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The Past, Present, and Future of Geostationary Meteorological Satellites: A Review

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Abstract: With the continuous development of remote-sensing technology, the capabilities and applications of geostationary meteorological satellites have gradually expanded. They play an important role in monitoring climate change, promoting the formulation of environmental protection policies, and reducing the damage caused by natural disasters. This study investigated the current state and emerging trends in geostationary meteorological satellite research. We systematically reviewed the developmental history of these satellites across various countries and performed a comparative analysis of their status over different periods. Using bibliometric methods, this study revealed the knowledge structure of the field and forecasted future trends. Key findings indicate that geostationary satellites have evolved through three generations, improving from spin to three-axis stabilization, and transitioning from single payloads to multiple instruments. Since 1990, a significant growth in publications and citations has been observed, particularly in the United States and China, reflecting increased global cooperation. The co-citation analysis identified 19 clusters, with machine learning emerging as a prominent focus. Over the last 65 years, research has shifted from theoretical analysis to the integration of artificial intelligence (AI) technologies, with leading regions transitioning from the United States and European Union to China. This study suggests four critical directions for future exploration: leveraging AI, enhancing weather analysis capabilities, utilizing multi-satellite data, and exploring ecological monitoring applications. This study offers valuable insights to researchers and policymakers by providing a comprehensive overview of the development and prospects within the field.

Key words: geostationary meteorological satellite; development history; bibliometric analysis; prospective tendency

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1 INTRODUCTION

Geostationary meteorological satellites operate in geostationary orbits approximately 35,800 km above the equator. They provide continuous, high-resolution observations of fixed areas, with the instrumental field-of-view fully covering weather systems on a scale of thousands of kilometers (Schmit et al. 2009). This capability has significantly enhanced numerical weather forecasting using meso- and small-scale models. Geostationary meteorological satellites equipped with advanced instruments such as multispectral imagers, infrared sensors, and microwave radiometers offer high-resolution and high-precision monitoring data. These products have been widely applied in various fields, including meteorology, oceanography, aviation, agriculture, water resources, and environmental management (Bayat et al. 2021).

Since the successful launch of the first geostationary environmental satellite, the geostationary operational environmental satellite (GOES)-A, by the United States on October 17, 1975, countries worldwide have gradually begun developing their own geostationary meteorological satellites and have vigorously promoted technological iterations (Duguay-Tetzlaff et al. 2015; Mecikalski and Bedka 2006). Significant progress has been made in the field of geostationary satellites in recent decades. This paper begins with an overview of the development of geostationary meteorological satellites, focusing on their historical development in major regions and countries such as the United States, Europe, Japan, and China. Then, a comprehensive comparative analysis of the development status of geostationary satellites in different regions and

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periods was conducted. Additionally, using bibliometric methods, this study provides a thorough investigation of geostationary meteorological satellites, revealing the complete structure of knowledge in this area and offering reliable predictions for future research trends. This study not only helps relevant researchers to understand the development trajectory of this field more clearly but also provides detailed and reasonable reference materials for management agencies and decision-makers.

2 HISTORICAL DEVELOPMENT OF GEOSTATIONARY METEOROLOGICAL SATELLITES

Table 1 summarizes a performance comparison of geostationary meteorological satellites from different countries across various periods. With over 50 years of rapid development, significant improvements have been made in the observation modes, design lifetimes, and payload performances of these satellites.

2.1 *United States*

The GOES series is a civil geostationary meteorological satellite program jointly developed by the National Oceanic and Atmospheric Administration (NOAA) and the National Aeronautics and Space Administration (NASA) (Mecikalski and Bedka 2006). From the launch of the first satellite, GOES-A, on October 17, 1975, to the current GOES-S, the series has progressed through three generations.

The GOES-A satellite was equipped with a visible infrared spin-scan radiometer, observing the Earth only 10% of the time (Xie et al. 2020). GOES-3, recognized as one of the oldest continuously operational spacecraft, was launched on June 16, 1978, and served for 38 years and 13 days before being decommissioned on June 29, 2016. Starting with GOES-4, an atmospheric sounder was incorporated to acquire vertical profiles of atmospheric temperature and humidity, enabling meteorologists to predict atypical weather phenomena, such as fog, snow, and sandstorms, more accurately (Wickramasinghe et al. 2020). However, because the imager and sounder shared the same optical system, use of the two instruments had to be alternated.

The second-generation GOES series began with GOES-I, launched on April 13, 1994. These satellites adopted three-axis stabilization for more flexible regional observations. Equipped with a five-channel imaging radiometer and a nineteen-channel atmospheric vertical sounder, they could freely alternate between routine and regional scanning modes (Duguay-Tetzlaff et al. 2015). Notable enhancements in spatiotemporal resolution, data volume, and continuity have allowed forecasters to improve tracking and locate potentially hazardous weather events, such as storms, lightning, and tornadoes.

As the inaugural satellite of the third-generation GOES series, GOES-R improved the temporal resolution of instrument imaging five-fold, spatial resolution four-fold, and spectral channels three-fold, delivering high-

Table 1. Performance comparison of geostationary meteorological satellites from different countries and regions across generations.

	Country/region		United States	Europe	Japan	China	Russia	India	Republic of Korea
First generation	Satellite		GOES-1	Meteosat-1	GMS-1	FY-2A	GOMS-1	INSAT-1	–
	Status stabilization mode		Spin	Spin	Spin	Spin	Three-axis	Three-axis	–
	Launch time		1975	1977	1977	1997	1994	1982	–
Second generation	Satellite		GOES-8	Meteosat-8	MTSAT-1R	–	–	INSAT-2	GEO-KOMSAT-1
	Status stabilization mode		Three-axis	Three-axis	Three-axis	–	–	Three-axis	Three-axis
	Launch time		1994	2002	2005	–	–	1999	2010
Next generation	Satellite		GOES-17	MTG-1	Himawari-9	FY-4A	Electro-L.N1	INSAT-3DR	GEO-KOMSAT-2A
	Status stabilization mode		Three-axis	Three-axis	Three-axis	Three-axis	Three-axis	Three-axis	Three-axis
	Launch time		2018	2021	2016	2016	2011	2016	2018
	Design lifespan (a)		15	8	10	7	10	10	10
	Imager	Spatial resolution (km) VIS	0.5	0.5	0.5	0.5	1	2	0.5
		Spatial resolution (km) IR	1–2	1–2	2	2–4	4	4–8	2
		Temporal resolution (min)	10	10	10	15	15	30	10
		Channels	16	16	16	14	10	6	16
	Detector	Spatial resolution/km	–	4	–	16	–	–	–
		Imaging time (min)	–	Full disk: 60	–	Region: 60	–	–	–
		Channels	–	1737	–	1648	–	–	–
	Lighting imaging sensor	Center wavelength (nm)	777.4	777.4	–	777.4	–	–	–
		Temporal resolution (min)	8	8	–	7.8	–	–	–

resolution satellite imagery every 30 s. With a design lifetime of 15 years, the GOES-R payloads include the advanced baseline imager, geostationary lightning mapper, solar ultraviolet imager, extreme ultraviolet and X-ray irradiance sensors, and space environment in situ suite (Boukabara et al. 2021). The subsequent launches of GOES-17 on March 1, 2018, and GOES-18 on March 1, 2022, enhanced the system capacity for near-real-time tracking of storms, lightning, wildfires, and other natural disasters affecting the western United States (Kurzrock et al. 2018). The latest satellite, GOES-19, launched on June 25, 2024, succeeded GOES-17 as the primary meteorological monitoring platform for the United States West Coast and Pacific region, marking a new phase in meteorological monitoring and space weather warning capabilities of the United States.

2.2 *Europe*

The European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) has launched twenty-four geostationary meteorological satellites since 1977, spanning three generations: Meteosat first generation (MFG), Meteosat second generation (MSG), and Meteosat third generation (MTG).

The first geostationary meteorological satellite, Meteosat-1, was launched in November 1977. With the successful launch of Meteosat-7 on September 2, 1997, seven satellites had been deployed, providing meteorological data for nearly three decades (Sowden et al. 2018). The rapid scanning service was established in September 2001. After being served by Meteosat-6 through 2006, responsibility was transferred to second-generation geostationary meteorological satellites. To support the international climate experiment, backup meteorological satellites began providing Indian Ocean data coverage service in 1998, which was initially handled by the Meteosat-5 imager. Meteosat-7 took over from 2007 onwards. In 2017, the service transitioned to Meteosat-8 (Giri et al. 2025).

The MSG series comprised four satellites: Meteosat-8, Meteosat-9, Meteosat-10, and Meteosat-11, each with a design lifetime of 7 years. Compared to the MFG, the MSG offers significantly larger data volumes and higher spatiotemporal resolution, supporting weather forecasting and climate monitoring in Europe and Africa. MSG satellites carried four instruments: the spinning enhanced visible and infrared imager (SEVIRI), geostationary Earth radiation budget (GERB), data collection system (DCS), and GEOS&R transponder (Xie et al. 2020). While maintaining spin stabilization, their performance showed substantial improvements: SEVIRI increased from three to twelve channels, visible channel resolution was 1 km, infrared and water vapor bands improved from 5 to 3 km, and temporal resolution was reduced from 30 to 15 min (Duguay-Tetzlaff et al. 2015).

The MTG represents the latest generation of geostationary meteorological satellites in Europe, jointly proposed by EUMETSAT and the European Space Agency. The system operates in a dual-satellite configuration comprising an MTG-I (imaging satellite) and MTG-S (sounding satellite). Six satellites are planned (four MTG-I and two MTG-S), with a design lifetime of 8 years, operating with three-axis stabilization, and stationed at 0° longitude (Wickramasinghe et al. 2020). The first MTG-I1 satellite was launched in December 2022 and carries primary payloads, including a flexible combined imager (FCI), a lightning imager, a data collection system, and a search and rescue system. The MTG-I1 FCI can complete a full-disk Earth scan in 10 min and scan the European region in 2.5 min. MTG-S1, which launched in July 2025, is equipped with an infrared sounder (IRS) and an ultraviolet-visible-near-infrared sounder. The IRS payload provides three-dimensional and instantaneous distributions of atmospheric water vapor and temperature (Wu et al. 2019).

2.3 *Japan*

Since the launch of its first geostationary meteorological satellite in 1977, Japan has developed three generations and successfully deployed nine satellites.

Their first-generation geostationary meteorological satellites, known as the geostationary meteorological satellite (GMS) series, were part of the global meteorological satellite system. The first satellite, GMS-1, was launched in July 1977 and began providing satellite data products on April 6, 1978. This was followed by the launches of GMS-2, GMS-3, GMS-4, and GMS-5, which primarily provided data services for the West Pacific and East Asia (Da 2015).

The Multi-functional Transport Satellite (MTSAT) is the second-generation geostationary meteorological satellite from Japan, with two satellites launched: MTSAT-1R and MTSAT-2. They employed a three-axis stabilization for attitude control. MTSAT provided cloud imagery, sea surface temperature, and water vapor distribution data for over 30 countries and regions. It produced Northern Hemisphere cloud imagery every 30 min across five spectral channels with a visible resolution of 1 km and infrared resolution of 4 km, proving to be more effective than GMS-5 in detecting low-level clouds and estimating nighttime sea-surface temperatures (Fang 2014).

Himawari-8 and Himawari-9 are the latest generation of geostationary meteorological satellites in Japan that utilize three-axis stabilization. Himawari-8 was successfully launched on October 7, 2014, increasing the observation frequency from every 30 min (with Himawari-7) to every 10 min, and reducing it further to 2.5 min for area scans around Japan. It carries three primary payloads: the advanced Himawari imager (AHI), space environment data acquisition monitor, and DCS (Bessho et al. 2016). The AHI is the main device on the satellite and features 16 channels. It has a visible light spatial resolution of 0.5–1 km and infrared resolution of 1–2 km, capable of collecting data on cloud cover, temperature, wind, precipitation, and aerosol distribution. Himawari-9 was

launched on November 2, 2016, and has a design life of 15 years. It currently works in tandem with Himawari-8 to form a dual-satellite observation system for meteorological monitoring in the Western Hemisphere (Giri et al. 2025).

2.4 *China*

China began the design and construction of its geostationary meteorological satellites and ground application system in the 1980s. The first geostationary meteorological satellite, FY-2A, was launched on June 10, 1997 (Wu et al. 2019). It was positioned over the equator at 105°E on June 17, initiating the era of operational on-orbit geostationary meteorological satellites in China.

Their first-generation geostationary satellites can be divided into three batches. The 01-batch satellites included two experimental satellites, FY-2A and FY-2B. The 02-batch comprised three operational satellites: FY-2C, FY-2D, and FY-2E. Compared to the 01-batch, the 02-batch saw significant technical improvements, primarily including an increase in the number of onboard scanning radiometer channels from three to five and enhanced onboard battery power supply capacity. The 03-batch included three satellites: FY-2F, FY-2G, and FY-2H. The main purpose of adding the 03-batch was to ensure a continuous and stable transition from first-generation geostationary meteorological satellites to the second generation (Yang et al. 2017).

FY-4A was the first second-generation geostationary meteorological satellite from China, adopting three-axis stabilization. It is equipped with four main payloads: Advanced geostationary radiation imager (AGRI), geostationary interferometric infrared sounder, lightning mapping imager, and space environment package (Zhang et al. 2019). Successfully launched on December 11, 2016, FY-4A achieved leapfrog enhancements in terms of payload quantity, number of spectral channels, spatiotemporal resolution, and satellite lifetime. It combines high-frequency, high-resolution, vertical sounding, and flexible regional observational capabilities. The raw data volume provided by FY-4A is 80 times that of the FY-2 series, and the processed product data reach 160 times that of FY-2 (Yang et al. 2017). The retrieval of various quantitative remote-sensing products, such as radiation, atmosphere, cloud, and surface data, has significantly enhanced services in weather analysis, numerical weather prediction, meteorological services, and space weather forecasting and warning. FY-4B, launched successfully on June 3, 2021, was the first operational new-generation geostationary meteorological satellite from China. It works in coordination with FY-4A to form a network observation system, further strengthening observation and response capabilities for medium- and small-scale disaster events.

2.5 *Russia*

In November 1994, Russia successfully launched its first experimental geostationary meteorological satellite, GOMS-1 (Electro1). This three-axis stabilized spacecraft had a design lifespan of three years and was outfitted with a two-band scanning radiometer. Despite its successful deployment, the satellite never entered operational service and was decommissioned in 2000 after unresolved technical issues prevented it from becoming fully functional (Boukabara et al. 2021).

The subsequent Electro-L program, which represented their second-generation capability, envisioned the deployment of a five-satellite fleet-designated Electro-L. N1 through N5. The launches of N1 in January 2011 and N2 in November 2015 initiated a constellation. Built for a ten-year service life, these satellites are equipped with a comprehensive instrument suite. The core payload is the imaging instrument MSU-GS, a sophisticated sensor system with ten spectral channels (three in visible light and seven in infrared), supplemented by a photoelectric geophysical instrument group (GGAK-E), data sampling system (ODSS), and dedicated search and rescue system (GEOSAR). Critical to its meteorological role, the MSU-GS scans the entire Earth disk every 15 min, achieving a visible-light spatial resolution of 1 km and infrared resolution of 1–4 km (Xie et al. 2020).

2.6 *India*

The first Indian communication and meteorological satellite, the INSAT-1A, was launched in 1982. The INSAT-1 series, developed and launched by the United States, comprised four satellites deployed between 1982 and 1990. These provided meteorological and communications services for India and the Indian Ocean region, carrying payloads such as the very high resolution radiometer (VHRR) and DCS, with resolutions of 2.7 (visible light) and 11 km (infrared) (Yang et al. 2017).

The INSAT-2 series followed with five satellites launched between 1992 and 1999. INSAT-2A and 2B were multi-purpose, whereas INSAT-2C and 2D focused on communication. The final satellite, INSAT-2E, paved the way for the INSAT-3 series and carried a three-channel charge-coupled device (CCD) camera with a 1 km resolution, along with the VHRR (Higuchi 2021).

The INSAT-3 series now supports communications, television broadcasting, meteorology, and search and rescue. Two operational satellites, INSAT-3D and INSAT-3DR, carry instruments including VHRR/2 (an improved version of the earlier VHRR), a CCD camera, the DCS, and the satellite-aided search and rescue system. VHRR/2 offers an enhanced resolution of 2 km in visible light and 8 km in other bands (Kim et al. 2020).

2.7 *Republic of Korea*

The first geostationary satellite of the Republic of Korea, GEO-KOMPSAT-1, was successfully launched in June 2010, offering integrated services for communications, ocean monitoring, and meteorology (Ouyang et al. 2021).

The GEO-KOMPSAT-2 series, the next-generation geostationary meteorological satellites, continued the weather and ocean environment observation mission of GEO-KOMPSAT-1, while improving the monitoring of the environmental conditions of the Korean Peninsula. The

program included two satellites: GEO-KOMPSAT-2A (meteorological) and GEO-KOMPSAT-2B (ocean and environmental). GEO-KOMPSAT-2A, launched on December 4, 2018, features a 10-year design lifetime and carries the advanced meteorological imager (AMI) and space environment monitor. The AMI has 16 spectral channels, completes full-disk scans in 10 min, and provides resolutions of 0.5 (visible light) and 1–2 km (infrared) (Boukabara et al. 2021). GEO-KOMPSAT-2B was launched in 2019.

3 BIBLIOMETRIC ANALYSIS

With the rapid development of geostationary meteorological satellite detection technology, scholars worldwide have published tens of thousands of scientific papers on geostationary meteorological satellite research over the past several decades. These publications comprise various types, such as articles, reviews, letters, notes, and proceedings. Notably, existing reviews on geostationary meteorological satellite research primarily rely on expert opinions and experience, often focusing on specific topics, while lacking a comprehensive understanding of the historical evolution of the entire research field. To address these shortcomings, this study employed bibliometric methods to conduct a comprehensive investigation of research on geostationary meteorological satellites. Based on literature records from the Web of Science (WoS) Core Collection database, this research aimed to reveal the complete structure of knowledge within the field of geostationary meteorological satellites, thereby providing quantitative analytical results for predicting future research trends.

3.1 *Research design and methodology*

The data used in this study were obtained from the WoS Core Collection database, which covers 1900 to the present. An investigation of the literature was undertaken on November 30, 2024, and revealed that the earliest publications in the field of geostationary meteorological satellites date to 1960. Therefore, the timeframe of the literature included in this study was set from January 1, 1960, to November 30, 2024. By using the search term "TS = (geostationary meteorological satellite OR geostationary satellite OR meteorological geostationary satellite)", a total of 9923 articles were identified. This study followed the conventional approach of using scientometric methods, excluding unrepresentative analysis objects such as conference papers, short communications, meeting abstracts, corrections, editorials, and book chapters (Chen et al. 2014; Liu 2023; Mingers and Leydesdorff 2015). Ultimately, a final dataset of 7292 original research papers and review articles was compiled and exported in "Full Record and Cited References" and "Plain Text" formats.

The project outlined in this study utilized an advanced version of CiteSpace 6.3 R3 to process and analyze the bibliometric data from the WoS database and generate dynamic visualizations (Chen 2006; Chen et al. 2012; Garfield 2009; Nalimov and Mul'chenko 1971; van Eck and Waltman 2010). CiteSpace is a powerful tool that helps researchers gain a comprehensive, efficient, and intuitive understanding of the foundational structures of geostationary meteorological satellite research.

In this study, we comprehensively collected published literature in the field of geostationary meteorological satellites, performed data cleaning, and generated a standardized dataset. The dataset was subjected to quantitative statistical analysis from four perspectives: fundamental attributes, collaboration, co-citation, and keyword co-occurrence. Notably, the collaboration analysis focused on three aspects, author, institution, and country, to investigate and assess the collaborative relationships among research entities. Co-citation analysis was conducted from three perspectives, i.e., references, authors, and journals, and the results provided a clear representation of the foundational knowledge structure in the research field. Keyword co-occurrence analysis offers a direct view of evolving research trends and helps identify current hotspots in the field.

3.2 *Fundamental attributes*

Figure 1 illustrates the annual trends in both publications and citations within the geostationary meteorological satellite research domain. Between 1960 and 1990, the number of publications and frequency of citations were notably low, suggesting a phase of stagnation in the progress of this domain. A closer examination reveals that this period coincides with the early stages of research on geostationary meteorological satellites, in which the field garnered limited attention and had only a small number of active researchers. In contrast, since 1990, there has been a steady and significant increase in both the volume of publications and the number of citations, signaling a phase of rapid growth and advancement. The most pronounced peak occurred in 2023, with 525 publications and 17002 citations. Furthermore, the annual citation rate in geostationary

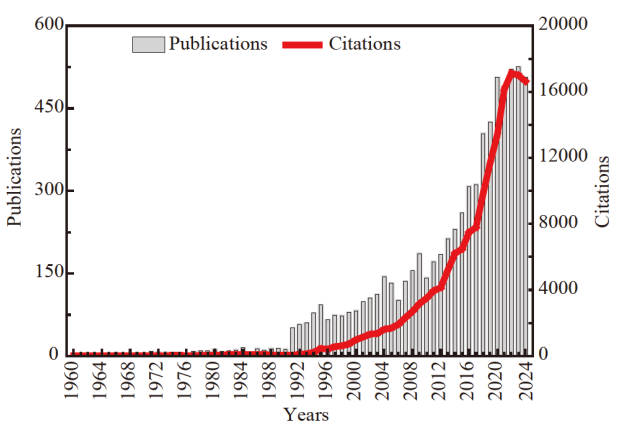


Figure 1. Annual trends in both publications and citations within the geostationary meteorological satellite research domain (gray shading represents publications, and red line represents citations). The data for 2024 is as of November 30.

meteorological satellite research has continued to show a sharp upward trajectory, indicating a sustained increase in interest and scholarly attention in this area. Notably, the WoS Core Collection database does not include abstracts before 1990. This means that the articles referenced in this study, prior to 1990, were primarily identified using title and author keywords. Considering the consistent year-to-year increase in the number of publications from 1960 to 2024, the overall impact on article statistics in this study is relatively minimal.

Figure 2 depicts the distribution of the 7292 articles across different WoS categories in this study. This analysis underscores the extensive representation of the WoS categories in geostationary meteorological satellite research. Among the categories, the top six are "Meteorology Atmospheric Sciences", "Remote Sensing", "Imaging Science Photographic Technology", "Environmental Sciences", "Geosciences Multidisciplinary", and "Astronomy Astrophysics". These categories collectively accounted for 2360, 1651, 1316, 1205, 1198, and 1005 articles, corresponding to 32.36%, 22.64%, 18.05%, 16.53%, 16.43%, and 13.78% of the entire dataset, respectively.

3.3 *Collaborative analysis*

By applying a collaborative analysis, a highly effective strategy was employed to reveal the complex structure of the scientific network. This approach helps identify prominent researchers at various levels, encompassing national links, institutional affiliations, and individual contributions (Chen et al. 2012).

3.3.1 AUTHOR COLLABORATION

Figure 3 presents a graphical representation of the intricate network of author collaborations, featuring 1633 distinct nodes (Appendices A1 and A2) and 2199 interconnected links (Appendix A3) from 1960 to 2024. The nodes symbolize individual authors, and the links illustrate the established collaborative relationships. The research field of "geostationary environment monitoring

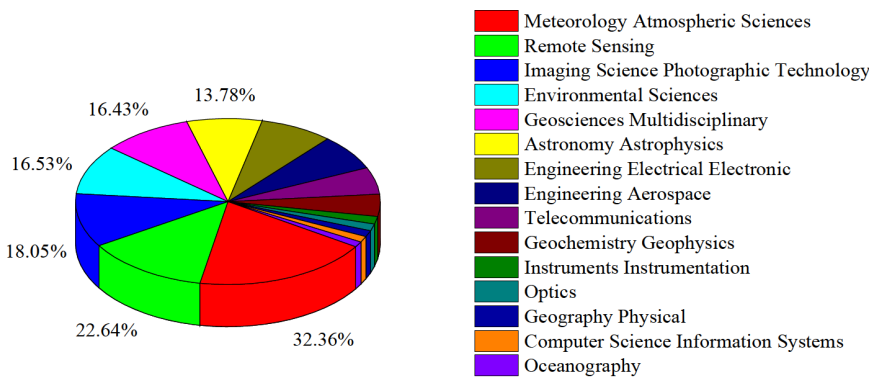


Figure 2. Distribution of 7292 articles across different WoS categories in this study.

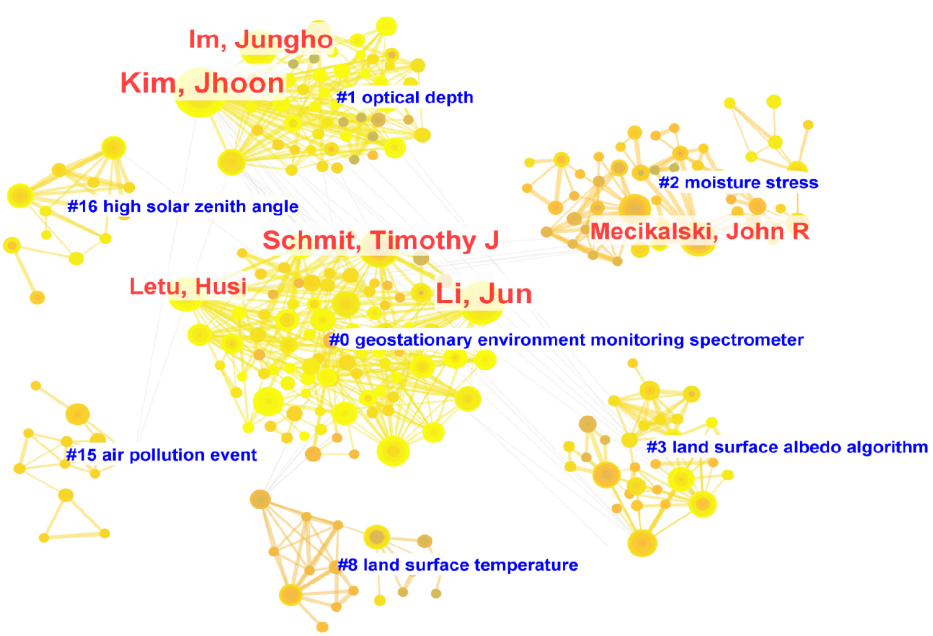


Figure 3. Analysis of author collaboration: a holistic perspective (nodes represent authors, and links show their collaborative relationships). The blue text indicates cluster labels (Appendix A4), and the red text highlights authors who are highly ranked based on their publication counts.

spectrometers" has attracted the most attention, leading to the emergence of a significant number of highly productive authors. Table 2 highlights the top ten authors in the area of geostationary meteorological satellite research, ranked based on their total number of publications. This also includes their betweenness centrality (Appendix A5) and the year of their first published work. Kim Jhoon, a distinguished researcher in the Department of Atmospheric Sciences at Yonsei University, has established himself as a leading expert in geostationary meteorological satellite research, with an impressive total of 64 published articles. Remarkably, Kim Jhoon possessed the highest centrality score of 0.09 and began his publication contributions to this field as early as 2007, highlighting him as a highly influential author in geostationary meteorological satellite research whose publications have significantly contributed to the advancement and evolution of this research domain. Li Jun, a senior scholar from the University of Wisconsin, held the second position in the ranking. Since 2007, he has published 62 articles on geostationary meteorological satellites. Additionally, his centrality score reached 0.06, indicating that his academic influence is relatively significant. Therefore, scholars who wish to gain a deeper understanding of the development trajectory and latest research trends in the field of geostationary meteorological satellites are advised to focus on publications from the research teams of both Kim Jhoon and Li Jun.

Table 2. Top ten authors ranked by publication volume.

Author	Publications	Centrality	Year
Kim Jhoon	64	0.09	2007
Li Jun	62	0.06	2007
Schmit Timothy J.	41	0.02	2006
Im Jungho	34	0.01	2018
Menzel W. P.	30	0.01	1983
Letu Husi	25	0.02	2019
Mecikalski John R.	25	0.01	2007
Min Min	22	0.00	2019
Minnis Patrick	22	0.01	2008
Pal P. K.	21	0.00	2010

3.3.2 INSTITUTION COLLABORATION

Figure 4 presents a graphical representation of the development of scholarly partnerships within a system of 746 nodes and 3901 connections. The nodes represent different institutions, and the links represent the established collaborations. Institutional collaboration has steadily expanded since 1973, reaching the highest point in global cooperation after 1991, a trend that has persisted to the present. This trend is closely linked to significant transformations in information exchange and travel practices driven by socioeconomic advancements. Furthermore, Fig. 4 shows that widespread and thorough academic cooperation among institutions worldwide has played a key role in driving the rapid progress in geostationary meteorological satellite research. Table 3 provides an overview of the top nine institutions that achieved significant success in academic publishing. Among the top-ranked entities, all but one were from the United States and China, with the exception of a single organization from France. This indicates that research institutions in the United States and China have an overwhelming dominance in geostationary meteorological satellite research, which is directly related to the large number of satellites owned by both countries.

3.3.3 COUNTRY COLLABORATION

Figure 5 shows the structure of international cooperative ties from 1960 to 2024, consisting of 118 nodes and 785 connections. The nodes are color-coded to indicate different publication periods, and the connections between them represent collaborative efforts among the various countries. Table 4 emphasizes the top ten countries based on both scholarly output and network centrality. As shown in Fig. 5 and Table 4, the United States is the clear

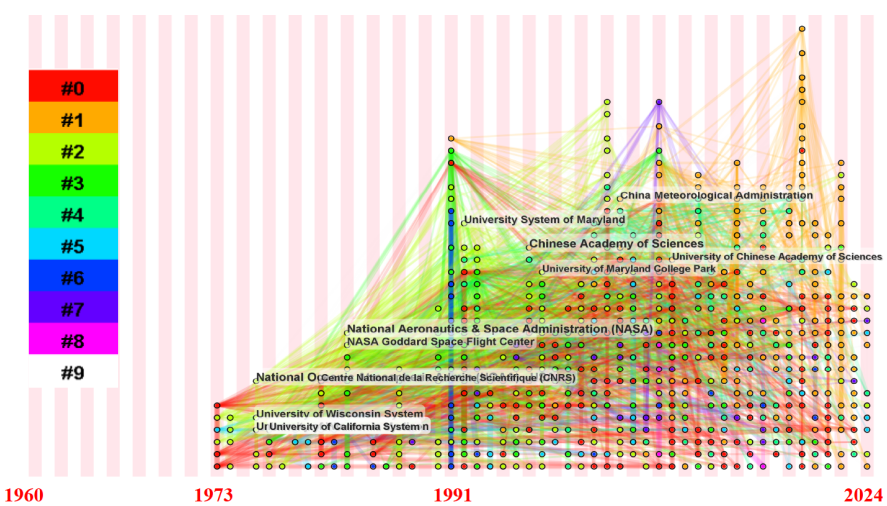


Figure 4. Analysis of institution collaboration: a time zone perspective (nodes represent institutions, and links depict their collaborative relationships).

Table 3. Top nine institutions ranked by publication volume.

Institution	Publications	First publication year	Country
NASA	953	1984	United States
NOAA	614	1977	United States
Chinese Academy of Sciences	597	1998	China
University of Wisconsin System	300	1977	United States
China Meteorological Administration	293	2005	China
University System of Maryland	261	1993	United States
University of Chinese Academy of Sciences	230	2009	China
University of California System	223	1978	United States
Centre National de la Recherche Scientifique (CNRS)	201	1982	France

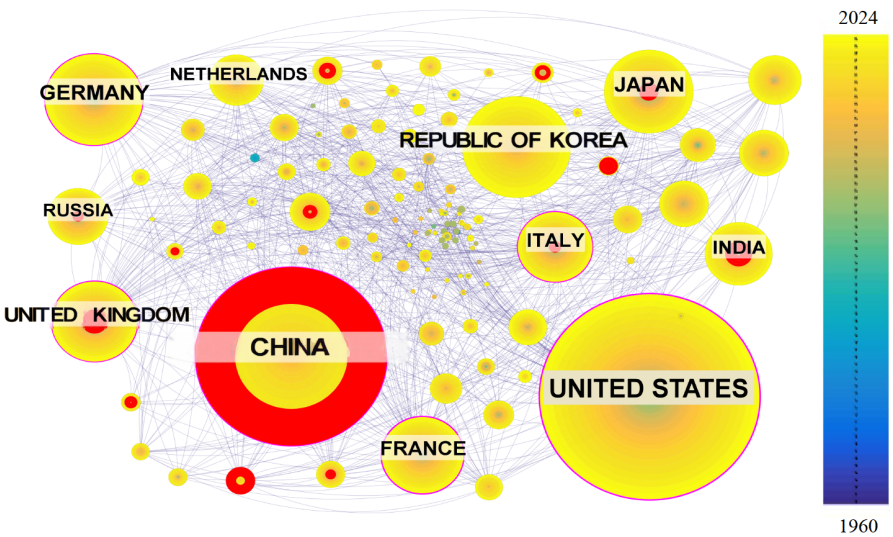


Figure 5. Analysis of country collaboration (nodes are color-coded by publication period, with connections representing international collaboration). The purple circles symbolize elevated betweenness centrality, whereas the red circles represent areas with high burstness.

Table 4. Top ten countries ranked by publication volume.

Country	Publications	Centrality
United States	2454	0.51
China	1785	0.10
Republic of Korea	616	0.02
Germany	519	0.13
Japan	450	0.05
United Kingdom	418	0.19
France	405	0.26
Italy	325	0.15
India	279	0.04
Russia	212	0.07

leader with 2454 publications, far outpacing the other countries. Following closely are China, the Republic of Korea, and Germany, with 1785, 616, and 519 publications, respectively. The United States not only has the highest number of publications but also has a betweenness centrality of 0.51, which is significantly higher than that of other countries. France ranks second in betweenness centrality, with a value of 0.26, although its publication count ranks seventh. This indicates that there is no apparent or substantial relationship between publication volume and betweenness centrality. Therefore, investigators conducting literature reviews should consider this issue. In general, developed countries demonstrate more advanced research achievements in the field of geostationary meteorological satellites, as reflected by their greater publication output and higher betweenness centrality scores than those of developing nations. The United States, Germany, the United Kingdom, France, and Italy play vital roles as key hubs that link two different areas of research in geostationary meteorological satellites, whereas China distinguishes itself as the most dynamic and focused epicenter for new developments in this field.

3.4 *Co-citation analysis*

Co-citation analysis is commonly grouped into three main classifications: reference-, author-, and journal-based (Chen et al. 2012). More details can be found in Appendix A6.

3.4.1 REFERENCE-BASED

This study employed a log-likelihood ratio weighting method to assess scholarly works and their sources, aiding in the assignment of accurate domain-specific labels for precise clustering and classification (Chen et al. 2014).

The co-citation structure consists of 2459 nodes and 5909 links (Fig. 6). This structure can be categorized into 19 distinct co-citation clusters, the comprehensive details of which are presented in Table 5. Notably, each cluster scored highly on the silhouette measure (Appendix A7), reflecting a strong degree of cohesion throughout the co-citation network. The categories assigned to the clusters in Table 5 reflect long-standing and recognized research areas within the field of geostationary meteorological satellites.

3.4.2 AUTHOR-BASED

The author-based co-citation study identified influential researchers with high citation counts and assessed the variety of topics covered in their contributions to the field of geostationary meteorological satellites. A unified author-based co-citation graph was constructed, consisting of 1919 nodes and 8489 links (Fig. 7). In this cohesive structure, each node represents a unique author, and the links denote the co-citation connections. The number of prominent authors in the field of geostationary meteorological satellites has grown steadily each year. Spanning the last 65 years, studies in this domain have demonstrated significant continuity and legacies. Table 6 displays a list of the top ten authors

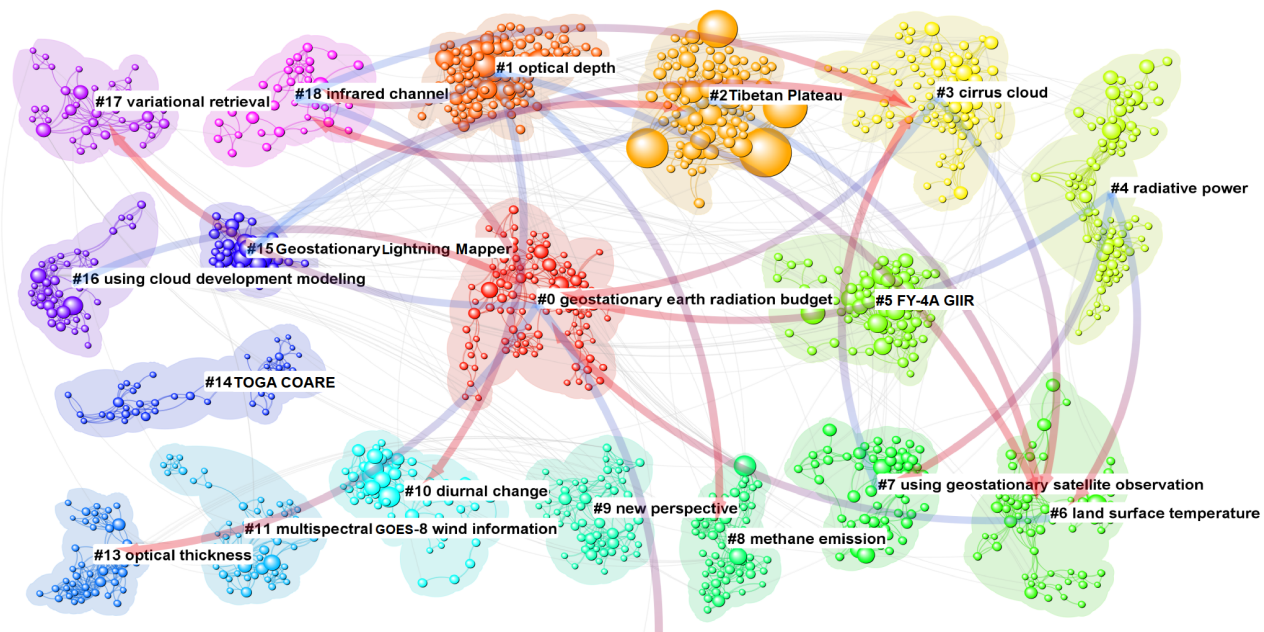


Figure 6. Analysis of reference co-citation (nodes represent references, and links show their co-citation relationships).

Table 5. Summary of the 19 leading clusters.

Cluster ID	Size	Silhouette	Average year	Label
0	106	0.987	2005	geostationary earth radiation budget
1	106	0.971	2018	optical depth
2	88	0.956	2018	Tibetan Plateau
3	84	0.932	2012	cirrus cloud
4	84	0.983	2011	radiative power
5	74	0.935	2017	FY-4A GIIR
6	69	0.983	2009	land surface temperature
7	63	0.972	2020	using geostationary satellite observation
8	57	0.99	2012	methane emission
9	57	0.966	1999	new perspective
10	54	0.989	2014	diurnal change
11	52	0.952	1995	multispectral GOES-8 wind information
13	48	0.996	1998	optical thickness
14	44	0.99	1992	TOGA COARE
15	43	0.934	2018	Geostationary Lightning Mapper
16	42	0.989	2005	using cloud development modeling
17	40	0.97	2000	variational retrieval
18	36	0.951	2011	infrared channel
42	9	0.996	2003	upper troposphere water vapor

ranked based on co-citation count, centrality, and burst intensity (Appendix A8). Individuals pursuing a career in the field of geostationary meteorological satellite studies can apply the information in Table 6 to identify widely cited authors, key influencers, and scholars involved in groundbreaking research, allowing them to strategically follow and monitor ongoing developments in the field.

3.4.3 JOURNAL-BASED

Similar to the author-based co-citation study, our journal-based co-citation study aimed to recognize widely referenced journals and assess their contributions to key themes in geostationary meteorological satellite research. We developed a consolidated network illustrating co-citation connections between journals, as shown in Fig. 8, consisting of 2005 nodes and 9414 links representing co-citation associations. In this structure, journals are depicted as nodes, and the connections reflect co-citation links. The results indicate that foundational journals in geostationary meteorological satellite research have consistently established co-citation links with later publications. This pattern is particularly evident in the leading ten clusters, highlighting the sustained conceptual coherence and intersection of research areas throughout time in journals pertaining to geostationary meteorological satellites. Fig. 9 presents a panoramic view of our journal-based co-citation study results. Each group was defined by its origin, timeline, termination, or ongoing status. The height of the peak represents the volume of publications by participants during a specific period, reflecting the level of involvement of a specific group. These findings suggest that optical depth is the most prominent cluster in ongoing research on geostationary meteorological satellites, drawing the most attention and leading to the most impactful discoveries. To offer a more detailed view of the analysis outcomes, Table 7 presents the order of the top ten journals based on co-citation count, centrality, and burst intensity, offering tailored recommendations for researchers at various stages of geostationary meteorological satellite research, whether in the planning phase or currently engaged in active studies, featuring highly cited journals, key influential publications, and cutting-edge subject-specific journals.

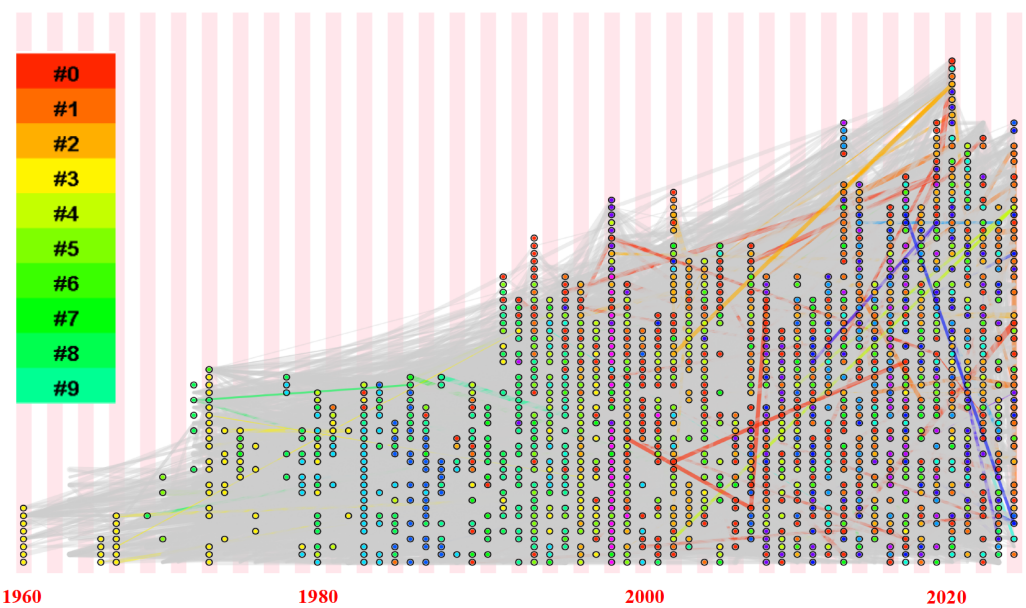


Figure 7. Analysis of author co-citation: a time zone perspective (nodes represent authors, and links show their co-citation relationships).

Table 6. Top ten authors ranked by co-citation count, centrality, and burst intensity.

Co-citation count	Centrality	Burst intensity
Schmit T. J. (560)	Wu Y. (0.14)	Hersbach H. (50.66)
Schmetz J. (448)	Berkofsky L. (0.10)	Menzel W. P. (49.16)
Bessho K. (433)	Bell G. D. (0.07)	Adler R. F. (41.54)
Menzel W. P. (353)	Ebert E. E. (0.06)	Kummerow C. (40.42)
Yang J. (310)	Kain J. S. (0.06)	Arkin P. A. (39.53)
Li J. (288)	Iwabuchi H. (0.06)	Yang J. (35.73)
Minnis P. (245)	Kalashnikova O. V. (0.06)	Minnis P. (30.06)
Kaufman Y. J. (244)	Jimenez J. (0.06)	Smith W. L. (29.8)
Stephens G. L. (220)	Kikuchi M. (0.05)	Bessho K. (29.71)
Holben B. N. (218)	Al-Saadi J. (0.05)	Schmetz J. (28.55)

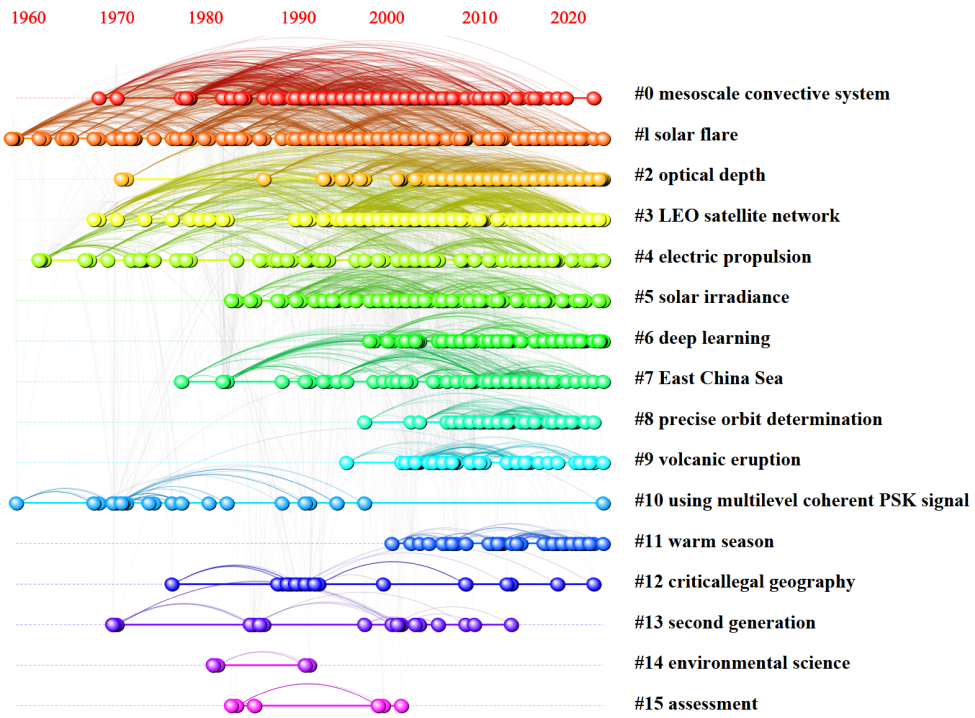


Figure 8. Analysis of journal-based co-citation: a timeline perspective (nodes represent journals, and links show their co-citation relationships).

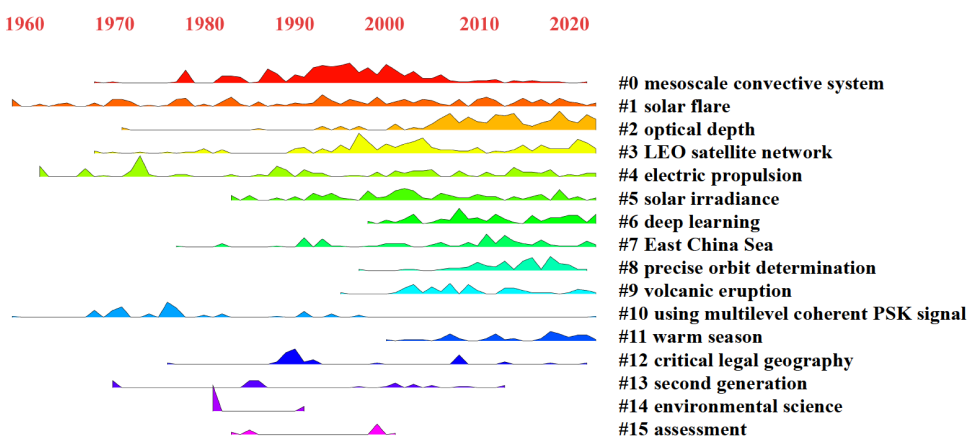


Figure 9. Analysis of journal-based co-citation: a landscape perspective.

Table 7. Top ten journals ranked by co-citation count, centrality, and burst intensity.

Co-citation count	Centrality	Burst intensity
J. Geophys. Res.-Atmos. (2957)	*Appl. Optics.* (0.10)	*J. Appl. Meteor.* (192.54)
B. Amer. Meteorol. Soc. (2711)	*J. Spacecraft Rockets* (0.07)	*J. Climate Appl. Meteor.* (115.89)
Geophys. Res. Lett. (2636)	*IEEE T. Aero. Elec. Sys.* (0.07)	*Mon. Wea. Rev.* (105.63)
IEEE T. Geosci. Remote (2107)	*Electron. Lett.* (0.06)	*J. Atmos. Sci.* (79.79)
Remote Sens. Environ. (2038)	*Adv. Space Res.* (0.05)	*Remote Sens.-Basel* (75.14)
Mon. Wea. Rev. (1685)	*Nature* (0.05)	*B. Amer. Meteorol. Soc.* (66.07)
J. Appl. Meteor. (1643)	*IEEE T. Commun.* (0.05)	*Planet Space Sci.* (51.25)
Int. J. Remote Sens. (1627)	*Astron. J.* (0.05)	*Atmosphere-Basel* (49.54)
Remote Sens.-Basel (1616)	*J. Appl. Meteor.* (0.05)	*J. Climate* (43.92)
J. Atmos. Sci. (1589)	*Geophys. Res. Lett.* (0.04)	*Earth Space Sci.* (43.57)

3.5 *Keyword co-occurrence*

To remain up-to-date with the most recent developments and central research themes in the field of geostationary meteorological satellites, a study of keyword co-occurrence (Appendix A6) was also conducted. Table 8 displays the findings of this study, which illustrate an intricate system of related keywords consisting of 907 nodes and 6051 connections. Early research hotspots in the field of geostationary meteorological satellites primarily focused on theoretical and methodological studies of atmospheric parameters (such as clouds, rainfall, radiation, precipitation, global precipitation, and parameterization). The regions with the most active research were mainly the United States and the European Union (e.g., the United States, GOES-R, and Meteosat). However, in recent years, the research focus in this field has gradually shifted toward the integration of AI technologies (such as machine learning, deep learning, and convolutional neural

Table 8. Twenty-four keywords with the most notable citation bursts (bold lines indicate the scope of keyword presence, and red coloring represents keyword burst significance or occurrence).

Keywords	Year	Strength	Begin	End	1960–2024
cloud	1991	26.99	1991	2007	
rainfall	1992	9.74	1992	2009	
surface	1990	10.22	1993	2003	
radiation	1993	9.82	1993	2010	
precipitation	1991	14.56	1999	2012	
parameterization	1997	10.55	2001	2012	
Meteosat	2001	9.91	2001	2016	
global precipitation	2003	11.26	2003	2011	
passive microwave	2002	12.84	2004	2015	
calibration	1991	9.47	2007	2013	
United States	1993	10.12	2009	2015	
GOES-R	2015	9.24	2015	2018	
solar flares	2015	9.76	2019	2021	
ecological monitoring	2017	12.58	2021	2024	
machine learning	2018	30.02	2021	2024	
combined retrieval	2019	10.37	2021	2024	
Fengyun	2020	17.87	2021	2024	
lightning monitoring	2020	11.26	2021	2024	
deep learning	2019	13.79	2022	2024	
land surface temperature	2014	11.33	2022	2024	
convolutional neural network	2019	11.33	2022	2024	
space weather	2019	10.26	2022	2024	
China	2010	9.95	2022	2024	
atmospheric modeling	2022	9.67	2022	2024	

networks) and their application across multiple scenarios and functions (such as solar flares, land surface temperature, and atmospheric modeling). Active research areas have also gradually shifted to China (e.g., Fengyun). Notably, the burst strength of the keyword "machine learning" peaked at 30.02, indicating that this is currently the most prominent research emphasis in the geostationary meteorological satellite field and a highly promising future research trend. This conclusion is consistent with the findings presented in Fig. 9.

4 POTENTIAL DIRECTIONS FOR FUTURE STUDY

Over the past 65 years, significant advancements have been made in the study of geostationary meteorological satellites. As our understanding grows, new directions and methodologies will inevitably arise. By combining the qualitative analysis in Section 2 and the quantitative analysis in Section 3, the following sections highlight the key areas that should be prioritized in future investigations.

4.1 *Application of AI technology in the field of geostationary meteorological satellite research*

Over the past several years, with the constant evolution of computing power, significant strides have been made in AI technology, particularly in addressing difficult tasks, such as autonomous driving, image processing, and machine translation, achieving impressive application results (Bengio et al. 2021; LeCun et al. 2015). With the rapid evolution of AI technology, countries worldwide have begun researching the unified application of AI, data management, computational power, and meteorological systems. AI is bringing innovative prospects to meteorology in two key areas: the acquisition and use of global and regional meteorological data and the forecasting and identification of extreme weather patterns and disasters. However, the application prospects of these materials are vast. Notably, AI has unparalleled advantages in big data processing; it not only synthesizes expert knowledge and experience, but also fully utilizes abstract forecasting insights that traditional statistical and numerical models are unable to capture (Ravuri et al. 2021).

Currently, the application of machine learning in the field of geostationary meteorological satellites is primarily focused on data analysis and processing (Cervantes et al. 2020; Chen et al. 2014; Zhang and Zhang 2022). With the rapid advancement of satellite instrumentation, the performance of satellite data has been significantly enhanced in terms of spectral bands, time, and spatial dimensions, resulting in a significant increase in data volume. For example, the data from the FY-4A and Himawari-8/9 satellites are hundreds of times larger than those from the previous FY-2 and MTSAT satellites (Bessho et al. 2016). However, multi-source observational data vary in form and physical meaning, and one of the current challenges is their effective integration. As a method for achieving AI, machine-learning algorithms can automatically learn and extract features, providing new insights for multi-source data fusion. Methods, such as random forests and convolutional neural networks, have been proven to significantly outperform traditional methods for monitoring severe weather. For example, Mecikalski et al. (2015) combined data from the GOES-R geostationary meteorological satellite and numerical weather prediction models to forecast convective environmental parameters, such as convective available potential energy, lifted index, and wind shear. By selecting 25 relevant factors and using logistic regression and random forests, they established a convective initiation (CI) probability forecasting system that effectively reduced the false alarm rate of CI in Europe. Ahijevych et al. (2016) applied random forests to integrate radar, satellite imagery, and numerical forecast data to predict the CI for the 0–2 h that immediately follow. The results showed that the model successfully detected over 99% of the developing systems (550 cases). Based on Himawari-8 satellite data, Han et al. (2019) used machine-learning methods such as decision trees, random forests, and logistic regression to build a CI forecasting model, achieving improved algorithm performance. Therefore, in situations where the physical mechanisms of certain weather phenomena are not yet fully understood, it is worthwhile to explore the use of machine-learning methods for big data mining and analysis of geostationary meteorological satellite observations.

4.2 *Application of geostationary meteorological satellites in weather analysis and numerical weather prediction*

Meteorological satellites, as important technological tools for weather observation, play an increasingly crucial and irreplaceable role in weather forecasting because of their capability for all-weather monitoring. Geostationary meteorological satellites, which have high frequency, high resolution, vertical probing, and mobile encryption capabilities, significantly enhance the monitoring, analysis, and forecasting of hazardous weather events, such as heavy rain, typhoons, and severe convective storms (Chen et al. 2019; Kim et al. 2020; Yang et al. 2017). Their high frequency and resolution allow for more accurate tracking of the development, evolution, and dissipation of phenomena such as rainstorms, snowstorms, typhoon clouds, and severe convective clouds, particularly improving the precision of typhoon location and intensity, as well as lightning monitoring (Liu and Zou 2015; Xu et al. 2025). Satellite cloud classification products, rainfall estimates, lightning monitoring, fog detection, dust storm detection, sea surface temperature, and cloud wind direction products greatly enhance the objective and quantitative monitoring and forecasting ability of hazardous weather events such as heavy rain, snowstorms, typhoons, severe convective storms, sea fog, and dust storms. Vertical probing capabilities provide a high spatiotemporal resolution of the atmospheric three-dimensional temperature and

humidity structure, filling the gaps in conventional sounding data. They extend atmospheric detection capabilities to sparsely populated areas and vast oceans, improving the initial conditions for numerical weather prediction and enhancing the precision of numerical weather models and fine-grained weather forecasting (Liu and Zhang 2016; Xu et al. 2023; Zhang et al. 2024). Additionally, products such as atmospheric instability indices derived from vertical probing can help detect changes in environmental conditions several hours before events such as heavy rain and severe convective weather, enabling the early identification of the precursors of extreme weather, which directly supports short-term weather forecasting and early warning systems. Furthermore, the mobile encryption monitoring capability of the satellite aids in the continuous high-frequency monitoring of high-impact or key areas for hazardous weather events, improves the early warning and response capabilities for major disasters in critical regions, and provides essential monitoring information and technical support for the timely release of warnings related to significant hazardous weather events. These points will continue to be important research directions for the development of geostationary meteorological satellites.

4.3 *Multi-satellite combined retrieval and application*

Because of the limited spatiotemporal coverage of a single geostationary meteorological satellite, the combined advantages of multiple geostationary satellites can be leveraged to obtain long-term continuous coverage data, thereby meeting the requirements of surface environment monitoring. For example, EUMETSAT integrates and analyzes data from all first- and second-generation Meteosat satellites to generate thematic climate data record products. The NOAA has made all GOES L1B data available since 1979, and the FY-2 and FY-4 series satellites from China have accumulated complete observations since 2005, both of which can be used to produce long-term continuous surface products. To obtain global coverage images, observations from geostationary meteorological satellites worldwide must be integrated (Xie et al. 2020). Govaerts et al. (2008) were the first to estimate surface albedo using data from five geostationary meteorological satellites from the European Union, the United States, and Japan, with a resulting error in the average surface albedo compared to MODIS data within 10%. Later, Lattanzio et al. (2013) attempted to generate continuous surface albedo climate data record products from the data of approximately 30 different geostationary satellite sensors in Europe, the United States, and Japan beginning with data from the early 1980s. In multi-satellite joint retrieval and application, the geometric and radiometric calibrations of different satellites must first be conducted to eliminate geometric and radiometric discrepancies between sensors.

However, owing to the geometric observation issues of geostationary satellites, image distortion is more significant in high-latitude regions, leading to poor imaging quality. Polar-orbiting satellites can compensate for this problem by providing better coverage in these areas. By combining data from both geostationary and polar-orbiting satellites, it is possible to effectively address the limitations of polar-orbiting satellites in extracting surface information, particularly the obstacles posed by cloud cover. Related fusion methods can be broadly divided into two categories. The first category directly involves the joint retrieval of surface parameters from data from both geostationary and polar-orbiting satellites. For example, Zhang et al. (2014) improved the lookup table method to retrieve shortwave and photosynthetically active radiation from MODIS, SEVIRI, MTSAT-1R, and GOES data. The second category relies primarily on geostationary satellite data to retrieve surface parameters, with polar-orbiting satellites providing supplementary information (Li et al. 2015). For example, Yang et al. (2013) used GOES geostationary satellite data along with passive microwave AMSR-E data to monitor snow cover in the eastern United States. The new fusion method provided more surface information than GOES data alone. Overall, research on the integration of geostationary and polar-orbiting satellites has focused on small regions or watershed scales, with relatively less work being conducted on national or continental scales, an area that warrants further investigation.

4.4 *Application of geostationary meteorological satellites in the ecological environment and space weather*

With the rapid development of the socioeconomic landscape, numerous ecological issues have emerged, such as soil erosion, land desertification, grassland degradation, and the increasing frequency of meteorological disasters under the backdrop of global climate warming, all of which severely hinder sustainable socioeconomic development. Satellite remote sensing is a primary data source for ecological monitoring and assessment. Geostationary meteorological satellites, with their high spatiotemporal resolution advantages, play an important role in this field (Zhang et al. 2019). Taking FY-4A as an example, the onboard AGRI can dynamically acquire high-precision parameters and information related to the ecological environment of the land. It is capable of monitoring vegetation changes, extracting information on grassland and desert areas and vegetation coverage, providing high-precision snow cover data, snow disaster monitoring and assessment, forest and grassland fire monitoring, large lake water body range extraction, drought monitoring, dynamic monitoring of the distribution and intensity changes of cyanobacterial blooms in inland lakes, and the spatiotemporal distribution and dynamic changes in urban thermal environments. Moreover, using the FY-4A satellite, aerosol optical thickness can be quantitatively retrieved, enabling dynamic monitoring of dust storm range and intensity, fog range and optical thickness, and haze distribution. Combined with data from the FY-3 satellite and ground-based observations, these multi-source data

can provide observational support for real-time atmospheric environmental monitoring and assessment.

In addition, data from space environment detectors aboard geostationary meteorological satellites can be used to monitor catastrophic space weather events and provide forecasting services for solar activity, geomagnetic conditions, and the ionosphere, upper atmosphere, and satellite operational environments (Choi et al. 2018; Lazzara et al. 2011; Seon et al. 2020). High-energy particle detection data can be directly used for the early warning of potential space weather threats, such as real-time monitoring and alerts for solar high-energy proton events. High-energy electron flux data can be used to calculate the probabilities of charge and discharge phenomena occurring in satellite instruments, thereby supporting satellite operation monitoring. The angular distribution of the particle flux helps to further our understanding of the dynamics of particles in a geostationary orbit, enhancing our knowledge of radiation-belt environments. Magnetic field detection data in geostationary orbit not only help verify global magnetic field models and assimilate them into high-precision models, but also serve to assess geomagnetic activity levels, estimate whether satellites pass through the magnetopause or bow shock, and provide input for space weather numerical forecast models, thus contributing to a deeper scientific understanding of solar wind-magnetosphere interactions. Warning and forecast indices related to satellite charging, single-particle events, radiation doses, and debris can also be obtained, enabling a comprehensive analysis of abnormal satellite or payload conditions to determine whether they are caused by space weather events, thereby ensuring the safe operation of satellites in orbit. Overall, space-weather monitoring and forecasting based on geostationary meteorological satellites provide security services for various fields, such as energy, communications, aviation, and space exploration. Key related technologies will also be the focus of future research.

5 CONCLUSION

This study investigated the current state and developing trends in geostationary meteorological satellite research. To achieve this, this study systematically reviewed the development history of geostationary meteorological satellites in various countries. A comprehensive comparative analysis of the status of geostationary meteorological satellite development in different regions and periods was conducted. Then, using bibliometric methods, a thorough investigation of the research in the field of geostationary meteorological satellites was performed, thereby revealing the complete structure of knowledge within this field. Finally, by combining qualitative and quantitative analyses, this study provides reliable predictions for future research trends. In summary, this study highlighted the following key findings:

(1) Geostationary meteorological satellites have evolved through three generations, with satellite platforms transitioning from spin stabilization to three-axis stabilization. Payloads have shifted from a single imaging instrument to multiple instruments working in parallel, resulting in significant improvements in temporal, spatial, and spectral resolutions in the latest generation of satellites.

(2) Between 1960 and 1990, research on geostationary meteorological satellites was limited; however, since 1990, there has been a significant increase in publications and citations, peaking in 2023, with 525 papers and 17002 citations. The United States and China have been key players in this rapid advancement, with strong involvement from institutions and authors in both countries. Over the past several decades, global cooperation among authors, organizations, and nations has become a dominant trend, greatly accelerating growth in this field.

(3) Nineteen unique co-citation clusters were identified by mapping the knowledge framework within the geostationary meteorological satellite studies. The co-citation analysis of authors and journals highlights consistent and gradual progress in the field from 1960 to 2024. Of particular note is the rise of machine learning as the most vibrant cluster in current geostationary meteorological satellite research, drawing significant interest and leading to significant developments.

(4) Over the past 65 years, research on geostationary meteorological satellites has evolved from a focus on the theoretical and methodological analyses of atmospheric parameters to a greater emphasis on integrating AI technologies and applying them to a variety of scenarios. Furthermore, the primary regions driving this research have gradually shifted from the United States and the European Union to China.

(5) Building on our analysis, this study identified four critical directions for future exploration in the field of geostationary meteorological satellites: leveraging AI technology, enhancing the role of these satellites in weather analysis and numerical weather prediction, utilizing combined data from multiple satellites, and exploring their applications in ecological monitoring and space weather.

From a practical perspective, this study offers essential support to researchers focusing on geostationary meteorological satellite studies by deepening their understanding of its development. However, there is room for further improvement. The references in this study were drawn primarily from the WoS Core Collection database. Although WoS is widely regarded as a trustworthy source, expanding the range of reference materials in future studies could potentially enhance the accuracy and depth of understanding within the field of geostationary meteorological satellites. Furthermore, incorporating independent experts to critically evaluate the findings in future studies may result in a more cohesive

and thorough analysis.

REFERENCES

Ahijevych, D., J. O. Pinto, J. K. Williams, and M. Steiner, 2016: Probabilistic forecasts of mesoscale convective system initiation using the random forest data mining technique. *Wea. Forecasting*, **31**, 581–599, https://doi.org/10.1175/WAF-D-15-0113.1.

Bayat, B., F. Camacho, J. Nickeson, M. Cosh, J. Bolten, H. Vereecken, and C. Montzka, 2021: Toward operational validation systems for global satellite-based terrestrial essential climate variables. *Int. J. Appl. Earth Obs.*, **95**, 102240, https://doi.org/10.1016/j.jag.2020.102240.

Bengio, Y., Y. Lecun, and G. Hinton, 2021: Deep learning for AI. *Commun. ACM*, **64**, 58–65, https://doi.org/10.1145/3448250.

Bessho, K., and Coauthors, 2016: An introduction to Himawari-8/9—Japan's new-generation geostationary meteorological satellites. *J. Meteor. Soc. Japan*, **94**, 151–183, https://doi.org/10.2151/jmsj.2016-009.

Boukabara, S. A., J. Eyre, R. A. Anthes, K. Holmlund, K. M. S. Germain, and R. N. Hoffman, 2021: The Earth-Observing Satellite Constellation: A review from a meteorological perspective of a complex, interconnected global system with extensive applications. *IEEE Geosci. Remote Sens. Mag.*, **9**, 26–42, https://doi.org/10.1109/MGRS.2021.3070248.

Cervantes, J., F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, 2020: A comprehensive survey on support vector machine classification: Applications, challenges and trends. *Neurocomputing*, **408**, 189–215, https://doi.org/10.1016/j.neucom.2019.10.118.

Chen, C. M., 2006: CiteSpace II: Detecting and visualizing emerging trends and transient patterns in scientific literature. *J. Amer. Soc. Inf. Sci. Technol.*, **57**, 359–377, https://doi.org/10.1002/asi.20317.

Chen, C. M., Z. G. Hu, S. B. Liu, and H. Tseng, 2012: Emerging trends in regenerative medicine: A scientometric analysis in CiteSpace. *Expert Opin. Biol. Ther.*, **12**, 593–608, https://doi.org/10.1517/14712598.2012.674507.

Chen, C. M., R. Dubin, and M. C. Kim, 2014: Emerging trends and new developments in regenerative medicine: A scientometric update (2000–2014). *Expert Opin. Biol. Ther.*, **14**, 1295–1317, https://doi.org/10.1517/14712598.2014.920813.

Chen, Y. P., K. M. Sun, C. Chen, T. Bai, T. Park, W. Wang, R. R. Nemani, and R. B. Myneni, 2019: Generation and evaluation of LAI and FPAR products from Himawari-8 advanced Himawari Imager (AHI) data. *Remote Sens.*, **11**, 1517, https://doi.org/10.3390/rs11131517.

Chen, Y. S., Z. H. Lin, X. Zhao, G. Wang, and Y. F. Gu, 2014: Deep learning-based classification of hyperspectral data. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, **7**, 2094–2107, https://doi.org/10.1109/JSTARS.2014.2329330.

Choi, W. J., and Coauthors, 2018: Introducing the geostationary environment monitoring spectrometer. *J. Appl. Remote Sens.*, **12**, 044005, https://doi.org/10.1117/1.JRS.12.044005.

Da, C., 2015: Preliminary assessment of the Advanced Himawari Imager (AHI) measurement onboard Himawari-8 geostationary satellite. *Remote Sens. Lett.*, **6**, 637–646, https://doi.org/10.1080/2150704X.2015.1066522.

Duguay-Tetzlaff, A., and Coauthors, 2015: Meteosat land surface temperature climate data record: Achievable accuracy and potential uncertainties. *Remote Sens.*, **7**, 13139–13156, https://doi.org/10.3390/rs71013139.

Fang, Z. Y., 2014: The evolution of meteorological satellites and the insight from it. *Adv. Meteor. Sci. Technol.*, **4**, 27–34, https://doi.org/10.3969/j.issn.2095-1973.2014.06.003. (in Chinese)

Garfield, E., 2009: From the science of science to Scientometrics visualizing the history of science with HistCite software. *J. Informetr.*, **3**, 173–179, https://doi.org/10.1016/j.joi.2009.03.009.

Giri, R. K., S. Prakash, R. Yadav, N. Kaushik, M. V. Shukla, P. K. Thapliyal, and K. C. Saikrishnan, 2025: A review of the global operational geostationary meteorological satellites. *Remote Sens. Appl.*, **37**, 101403, https://doi.org/10.1016/j.rsase.2024.101403.

Govaerts, Y., and A. Lattanzio, 2008: Estimation of surface albedo increase during the eighties Sahel drought from Meteosat observations. *Global Planet. Change*, **64**, 139–145, https://doi.org/10.1016/j.gloplacha.2008.04.004.

Han, D., J. Lee, J. Im, S. Sim, S. Lee, and H. Han, 2019: A novel framework of detecting convective initiation combining automated sampling, machine learning, and repeated model tuning from geostationary satellite data. *Remote Sens.*, **11**, 1454, https://doi.org/10.3390/rs11121454.

Higuchi, A., 2021: Toward more integrated utilizations of geostationary satellite data for disaster management and risk mitigation. *Remote Sens.*, **13**, 1553, https://doi.org/10.3390/rs13081553.

Kim, J., and Coauthors, 2020: New era of air quality monitoring from space: Geostationary environment monitoring spectrometer (GEMS). *Bull. Amer. Meteor. Soc.*, **101**, E1–E22, https://doi.org/10.1175/BAMS-D-18-0013.1.

Kurzrock, F., S. Cros, F. C. Ming, J. A. Otkin, A. Hutt, L. Linguet, G. Lajoie, and R. Potthast, 2018: A review of the use of geostationary satellite observations in regional-scale models for short-term cloud forecasting. *Meteor. Z.*, **27**, 277–298, https://dx.doi.org/10.1127/metz/2018/0904.

Lattanzio, A., and Coauthors, 2013: Land surface albedo from geostationary satellites: A multiagency collaboration within SCOPE-CM. *Bull. Amer. Meteor. Soc.*, **94**, 205–214, https://doi.org/10.1175/BAMS-D-11-00230.1.

Lazzara, M. A., A. Coletti, and B. L. Diedrich, 2011: The possibilities of polar meteorology, environmental remote sensing, communications and space weather applications from Artificial Lagrange Orbit. *Adv. Space Res.*, **48**, 1880–1889, https://doi.org/10.1016/j.asr.2011.04.026.

LeCun, Y., Y. Bengio, and G. Hinton, 2015: Deep learning. *Nature*, **521**, 436–444, https://doi.org/10.1038/nature14539.

Li, L., X. Z. Xin, H. L. Zhang, J. F. Yu, Q. H. Liu, S. S. Yu, and J. G. Wen, 2015: A method for estimating hourly photosynthetically active radiation (PAR) in China by combining geostationary and polar-orbiting satellite data. *Remote Sens. Environ.*, **165**, 14–26, https://doi.org/10.1016/j.rse.2015.03.034.

Liu, Y., and X. L. Zou, 2015: Impact of 4DVAR assimilation of AIRS total column ozone observations on the simulation of Hurricane Earl. *J. Meteor. Res.*, **29**, 257–271, https://doi.org/10.1007/s13351-015-4058-2.

Liu, Y., and W. Zhang, 2016: Improved hurricane forecasting from a variational bogus and ozone data assimilation

(BODA) scheme: Case study. *Meteor. Atmos. Phys.*, **128**, 715–732, https://doi.org/10.1007/s00703-016-0460-2.

Liu, Y., 2023: Research progress and trends in the field of satellite ozone from 2005 to 2023: A bibliometric review. *Atmosphere*, **14**, 1245, https://doi.org/10.3390/atmos14081245.

Mecikalski, J. R., and K. M. Bedka, 2006: Forecasting convective initiation by monitoring the evolution of moving cumulus in daytime GOES imagery. *Mon. Wea. Rev.*, **134**, 49–78, https://doi.org/10.1175/MWR3062.1.

Mecikalski, J. R., J. K. Williams, C. P. Jewett, D. Ahijevyc, A. LeRoy, and J. R. Walker, 2015: Probabilistic 0–1-h convective initiation nowcasts that combine geostationary satellite observations and numerical weather prediction model data. *J. Appl. Meteor. Climatol.*, **54**, 1039–1059, https://doi.org/10.1175/JAMC-D-14-0129.1.

Mingers, J., and L. Leydesdorff, 2015: A review of theory and practice in scientometrics. *Eur. J. Oper. Res.*, **246**, 1–19, https://doi.org/10.1016/j.ejor.2015.04.002.

Nalimov, V. V., and Z. M. Mul'chenko, 1971: Measurement of Science. Study of the Development of Science as an Information Process; U.S. Air Force Systems Command, Foreign Technology Division: Virginia, CA, USA.

Ouyang, H. X., Z. K. Qin, and J. Li, 2021: Impact of assimilating advanced Himawari Imager channel 16 data on precipitation prediction over the Haihe River Basin. *Atmosphere*, **12**, 1253, https://doi.org/10.3390/atmos12101253.

Ravuri, S., and Coauthors, 2021: Skilful precipitation nowcasting using deep generative models of radar. *Nature*, **597**, 672–677, https://doi.org/10.1038/s41586-021-03854-z.

Schmit, T. J., J. Li, S. A. Ackerman, and J. J. Gurka, 2009: High-spectral- and high-temporal-resolution infrared measurements from geostationary orbit. *J. Atmos. Ocean. Technol.*, **26**, 2273–2292, https://doi.org/10.1175/2009JTECHA1248.1.

Seon, J., and Coauthors, 2020: Particle detector (PD) experiment of the Korea space environment monitor (KSEM) aboard geostationary satellite GK2A. *Space Sci. Rev.*, **216**, 13, https://doi.org/10.1007/s11214-020-0636-4.

Sowden, M., U. Mueller, and D. Blake, 2018: Review of surface particulate monitoring of dust events using geostationary satellite remote sensing. *Atmos. Environ.*, **183**, 154–164, https://doi.org/10.1016/j.atmosenv.2018.04.020.

van Eck, N. J., and L. Waltman, 2010: Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, **84**, 523–538, https://doi.org/10.1007/s11192-009-0146-3.

Wickramasinghe, C., L. Wallace, K. Reinke, and S. Jones, 2020: Intercomparison of Himawari-8 AHI-FSA with MODIS and VIIRS active fire products. *Int. J. Digit. Earth*, **13**, 457–473, https://doi.org/10.1080/17538947.2018.1527402.

Wu, D., J. Chen, M. Shi, B. Y. Qin, and S. Y. Li, 2019: Reconstruction of land surface temperature time-series datasets of FY-2F based on Savitzky-Golay filter. *Remote Sens. Nat. Res.*, **31**, 59–65, https://doi.org/10.6046/gtzyyg.2019.02.09. (in Chinese)

Xie, Y. Q., Y. Xue, J. Guang, L. L. Mei, L. She, and Y. Li, 2020: Deriving a global and hourly data set of aerosol optical depth over land using data from four geostationary satellites: GOES-16, MSG-1, MSG-4, and Himawari-8. *IEEE T. Geosci. Remote*, **58**, 1538–1549, https://doi.org/10.1109/TGRS.2019.2944949.

Xu, D. M., X. W. Zhang, Z. Q. Liu, and F. F. Shen, 2023: All-sky infrared radiance data assimilation of FY-4A AGRI with different physical parameterizations for the prediction of an extremely heavy rainfall event. *Atmos. Res.*, **293**, 106898, https://doi.org/10.1016/j.atmosres.2023.106898.

Xu, D. M., H. Chen, Y. F. Chen, D. Q. Liu, F. Ge, X. Y. Ye, Q. L. Sun, and F. F. Shen, 2025: The impact of assimilating FY-3D Microwave Humidity Sounder II radiance data on the analysis and forecast of two advection fog cases. *Atmos. Res.*, **323**, 108162, https://doi.org/10.1016/j.atmosres.2025.108162.

Yang, J., Z. Q. Zhang, C. Y. Wei, F. Lu, and Q. Guo, 2017: Introducing the new generation of Chinese geostationary weather satellites, Fengyun-4. *Bull. Amer. Meteor. Soc.*, **98**, 1637–1658, https://doi.org/10.1175/BAMS-D-16-0065.1.

Yang, J. T., L. M. Jiang, J. M. Pan, and L. X. Zhang, 2013: Study of monitoring snow cover using GOES geostationary satellite and AMSR-E. *Remote Sens. Technol. Appl.*, **28**, 920–927. (in Chinese)

Zhang, L. F., and L. P. Zhang, 2022: Artificial intelligence for remote sensing data analysis: A review of challenges and opportunities. *IEEE Geosci. Remote Sens. Mag.*, **10**, 270–294, https://doi.org/10.1109/MGRS.2022.3145854.

Zhang, P., and Coauthors, 2019: General comparison of FY-4A/AGRI with other GEO/LEO instruments and its potential and challenges in non-meteorological applications. *Front. Earth Sci.*, **6**, 224, https://doi.org/10.3389/feart.2018.00224.

Zhang, X. T., S. L. Liang, G. Q. Zhou, H. R. Wu, and X. Zhao, 2014: Generating Global LAnd Surface Satellite incident shortwave radiation and photosynthetically active radiation products from multiple satellite data. *Remote Sens. Environ.*, **152**, 318–332, https://doi.org/10.1016/j.rse.2014.07.003.

Zhang, X. W., D. M. Xu, J. Z. Min, H. Li, F. F. Shen, and Y. H. Lei, 2024: A machine learning-based bias correction scheme for the all-sky assimilation of AGRI infrared radiances in a regional OSSE framework. *IEEE T. Geosci. Remote*, **62**, 5407314, https://doi.org/10.1109/TGRS.2024.3427434.

Citation: Liu, Y., and X. Y. Chen, 2026: The Past, Present, and Future of Geostationary Meteorological Satellites: A Review. *J. Trop. Meteor.*, **32**, 211–228, https://doi.org/10.3724/j.1006-8775.2026.010.

APPENDIX

APPENDIX A COMMONLY USED TERMS AND THEIR MEANINGS IN SCIENTOMETRIC MAPPING

When assessing the network visualization produced by CiteSpace, several critical visual patterns and aspects require careful attention.

Appendix A1 Node size

Node size often reflects significance or prominence within a network. The larger nodes signify highly cited papers, leading researchers, or essential concepts.

Appendix A2 Node color and tree rings

Node colors and tree rings, particularly red, can have important meanings. Color reflects the time period of a publication or the development of a concept. Red tree rings signal citation bursts, implying that this work has attracted growing attention during a certain timeframe.

Appendix A3 Links between nodes

The links between the nodes illustrate various relationships, including co-authorship, co-citation, and shared themes. The quantity and intensity of these connections reflect the level of association.

Appendix A4 Clusters

Clusters are sets of strongly connected nodes that often signify a particular theme or topic within a broader field of study. Larger clusters indicate higher levels of research activity or greater interest in a specific area.

Appendix A5 Betweenness centrality

Betweenness centrality is a metric applied to each node in a network to assess the probability of a randomly selected shortest path passing through that node. A node with a high betweenness centrality typically resides between two significant communities or subnetworks, which is the origin of its name.

In CiteSpace, nodes with elevated betweenness centrality are represented by a purple ring, with the ring thickness indicating the level of betweenness centrality.

In CiteSpace, betweenness centrality is applied through the lens of structural hole theory, which was initially designed for social network analysis. A key insight of this theory is that the presence or absence of connections within a network helps identify the most influential nodes. CiteSpace extends these ideas to uncover boundary-crossing opportunities and new broker roles for academic publications.

Appendix A6 Co-citations and co-occurrences

Co-citation occurs when two references are cited together in a third article. Traditionally, if both references are mentioned elsewhere in an article, they are deemed to be co-cited. However, if the full text of a third article is available, it is possible to focus on specific sections, paragraphs, or sentences.

References can be cited for various reasons and serve multiple purposes. However, the way in which a reference is cited often aligns with the underlying concept.

Co-citation is a localized event involving two references. These events collectively help establish a network of co-cited references. One of the main objectives of CiteSpace is to study these networks to detect patterns and trends related to the structure and development of underlying scientific literature.

A co-citation link between references R1 and R2 was illustrated within a visual network based on the degree of similarity between the two references. For example, we consider a dataset of 10000 articles, where R1 is referenced by 100 articles, and R2 is cited by 100. Similarity is determined by identifying articles that refer to both R1 and R2. If 30 articles cite both references, the similarity is calculated by dividing this number by the square root of the product of 100 and 100, yielding a value of 100. Thus, the co-citation weight or similarity is 0.30. The highest possible similarity (1.00) occurs when the two sets of 100 citing articles completely overlap, whereas the lowest (0.00) occurs when no article cites either R1 or R2. CiteSpace offers various approaches to measure this similarity.

Co-citation is a specific type of co-occurrence that can involve the simultaneous occurrence of words (co-words) or other entities, such as co-authors or author-based co-citations.

Appendix A7 Silhouette scores

The silhouette score of a cluster evaluates how similar its members are to each other, helping to determine whether they are grouped based on shared traits. In simple terms, a cluster with a higher silhouette score is viewed as being more significant than a cluster with a lower score.

Appendix A8 Burst detection

A burst describes a rapid increase in the occurrence of a specific kind of event, such as a sharp uptick in citations of a Nobel Prize-winning paper.

CiteSpace allows for burst detection across various event types, including (1) phases, whether single- or multi-word, derived from the title, abstract, or other sections of a publication; (2) citation counts for referenced works over time; (3) the occurrence rates of keywords over time; and (4) the publication count of an author, institution, or country.

In CiteSpace, users have the option to modify the burst detection settings using the Burstness tab in the Control Panel. For example, lowering the gamma value enhances sensitivity, allowing more burst items to be detected. Conversely, increasing the minimum duration helps decrease the number of burst items identified.