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EDITED BY
Ying Jing,
Zhejiang University, China

REVIEWED BY
Liangzhi Li,
Chang'an University, China
Mengling Qiao,
The Chinese University of Hong Kong, China
Jiawei Zhu,
Central South University, China

*CORRESPONDENCE
Lijun Xing,
ljxing2019@hubu.edu.cn

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Research on the spatiotemporal distribution and evolution of remote sensing: A data-driven analysis

Yu Liu[1], Xi Kuai[2,3], Fei Su[4], Shaochen Wang[5], Kaifeng Wang[1] and Lijun Xing[6]*

[1]Institute of Environment and Development, Guangdong Academy of Social Sciences, Guangzhou, China, [2]Shenzhen Key Laboratory of Spatial Information Smart Sensing and Services, Research Institute for Smart Cities, Shenzhen University, Shenzhen, China, [3]Peng Cheng Laboratory, Shenzhen, China, [4]School of Surveying and Geo-Informatics, Shandong Jianzhu University, Jinan, China, [5]School of Resource and Environmental Sciences, Wuhan University, Wuhan, China, [6]Key Laboratory of Regional Development and Environmental Response, Hubei University, Wuhan, China

The development of remote sensing technology largely reflects the scientific research level of a country or region. Given that the quantity and quality of research works are important indicators for scientific prowess evaluation, exploratory spatial data analysis and scientometric analysis of remote sensing work published from 2012 to 2021 were performed in this study, utilizing the Web of Sciences database. This study probed the spatial distribution and spatiotemporal evolution at the country/regional level to reveal the spatiotemporal characteristics of knowledge spillover in remote sensing. According to the results, the global spatial distribution of research output in remote sensing presented a significant dispersion; the United States and China were the most active countries. During the study period, *Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery* was one of the most influential studies, both in the field of remote sensing and in the whole scientific community. With respect to the spatial evolution of research output in remote sensing, the gap between continents and the regional imbalance showed a downward trend, while Asia ranked first in the intracontinental disparity and Europe ranked last. For relevant countries/regions and institutions trying to optimize the spatial allocation of scientific and technological resources to narrow regional disparities, this study provides fundamental data and decision-making references.

KEYWORDS

remote sensing, spatiotemporal distribution, research paper, regional disparity, paper output

1 Introduction

Remote sensing is a technology used to observe and explore target objectives and natural phenomena over long distances (Weng, 2012; Han et al., 2014; Cheng et al., 2017). Remote sensing technology can be used to objectively and accurately obtain timely information about various targets. Over the past few decades, remote sensing has been utilized to observe natural resources and Earth's environment from multiple layers to collect data from areas of Earth to space for application in diverse fields, such as the atmosphere, ocean, resources, environment, economy, agriculture, forestry, urban areas, disaster rescue, and the military (Chen et al., 2006; Chang et al., 2011; Jewiss et al., 2020). Moreover, remote sensing is a new interdisciplinary subject that is integrated with surveying and mapping, space science, electronic science, geosciences, and computer science (Fuentes, 2006; Lary et al., 2016; Tapete, 2018). The development level of remote sensing represents the level of scientific research in a country/region (Soille and Pesaresi, 2002; Andrefouet and Riegl, 2004). Therefore, an increasing number of countries are investing increasing amounts of money and effort in remote sensing research.

Over the past decades, some countries/regions have been in leading positions in remote sensing-related research, and their research results have influenced the development trend of the industry (Kussul et al., 2017; Mikhaylov et al., 2021). Some countries/regions have come to the forefront and have become a new force in remote sensing-related research and are expanding their field. Other countries have turned from field leaders to followers for various reasons (Zhu et al., 2017; Goga et al., 2019). These phenomena reflect the change in scientific research power in remote sensing among countries and the changes in national scientific and technological strength (Nogueira et al., 2016; Zhang et al., 2016). An in-depth study of the phenomena is required not only for researchers to get a quick overview of the history and current situation of remote sensing research but also for related countries/regions to better predict the trend of remote sensing research development and then make remote sensing development plans that really meet their national conditions (Zou et al., 2015; Nogueira et al., 2016). However, the broadness of remote sensing research fields, the diversity of subfields, the differences in disciplinary backgrounds, and the limited personal energy of scholars make it quite difficult to systematically and comprehensively summarize the national/regional strength changes in remote sensing research without high-quality data sources and reliable quantitative analysis methods.

Fortunately, tens of thousands of remote sensing-related research works have been published by researchers in the past few decades. These research works are important carriers and the main transmitters for research achievement, providing information about the research history, current situation, and development trends of the realm and sub-realms (Guarino, 1995; Qiu and Shen, 2021). Previous studies show that the output and quality of research are important indicators to measure the level of national science and technology (Price, 1963; Bourdieu, 2004). Research work data are characterized by easy accessibility and massive volume. In addition, the existing academic databases have collated the research data so that researchers can easily access high-quality studies. On the other hand, quantitative analysis is a mathematical method in scientometrics to measure research results, describe the scientific system structure and analyze the inner operating mechanism of the scientific system. This method can be employed to reveal the spatial and temporal characteristics of scientific development and explore the quantitative regular characteristics of scientific activities in human society. And in the field of spatial data analysis, exploratory spatial data analysis methods have been introduced into fields such as library intelligence and scientometrics in recent years, demonstrating their applicability in the exploration of the spatial differences and evolution of research in related disciplines/fields. More importantly, according to recent studies, research on the spatial distribution of research output can not only help discover the spatial distribution of professional knowledge but also unearth the external causes of regional gaps in research output (Ma et al., 2019a).

In summary, based on the Web of Science (WoS) database, this study presents a study focusing on the output of research works in remote sensing at different levels, such as the distribution of, spatial differences in the aggregation of the global level, differential evolution, and polarization and spatial aggregation between different local areas. The results of this study can not only provide an important basis for related resource allocation and decisive references for scientific macro arrangement in relevant countries/regions, which is conducive to regional science development and thus reduce the regional gap in remote sensing fields. The rest of this study is organized as follows. Section 2 describes the data collection and preparation. Then, the research methodology and analysis of the experimental results are introduced. The conclusion is summarized in the final section.

2 Data collection

On the basis of a web development platform, the WoS is a large, comprehensive citation indexing database developed by Thomson Reuters. Through this database, users can retrieve information about literature in the natural sciences, social sciences, arts, and humanities (Mongeon and Paul-Hus, 2016). The WoS provides relatively complete bibliographic and citation information, including the title, author, abstract, keywords, date, author address, subject category, and reference list (Harzing and Alakangas, 2016). Importantly, bibliographic and citation data in the WoS can be downloaded to track the history and reveal the characteristics of a research field. Given the above, the WoS has been adopted as a data source for many scientometric studies.

The data used in this study were collected from the WoS to investigate the spatial distribution and evolution pattern of the research work output in remote sensing. The data acquisition process was as follows: First, the search function of the WoS database was utilized, and "remote sensing" was selected as the search term. Second, the publication time was set as 2012–2021 (download date: 2 November 2021), the literature type was set as "article," and the language category was set as English. Finally, 13,057 pieces of data were obtained after removing duplicate data.

3 Method

In this study, the standard deviation and coefficient of variation were used to measure the absolute and relative differences between countries/regions and the Gini coefficient was used to explore intra- and intercontinental differences. Exploratory spatial data analysis (ESDA) was performed to reveal the spatial and temporal characteristics of knowledge spillover in remote sensing fields.

3.1 Coefficient of variation

The standard deviation is the arithmetic square root of the variance, which is an absolute indicator of the degree of dispersion of each observation (Lee et al., 2015). The calculation formula is as follows:

$$S = \sqrt{\sum_{i=1}^{n} \frac{(x_i - \bar{x})^2}{n-1}}. \tag{1}$$

The coefficient of variation (CV) is the ratio of the standard deviation to the mean value, which is a relative index reflecting the dispersion of observed values (Shechtman, 2013). The mathematical expression is as follows:

$$CV = \frac{1}{\bar{x}} \sqrt{\sum_{i=1}^{n} \frac{(x_i - \bar{x})^2}{n-1}}, \tag{2}$$

where x_i is the output of remote sensing research in country/region i, $\bar{x}$ is the average output of remote sensing research, and n is the number of countries/regions.

3.2 Gini coefficient

The Gini coefficient is an index originally used in economics that is mainly used for income gap measurement. The value of the Gini coefficient is in the range of 0–1. The closer the value is to 1, the larger the income gap is, while the closer it is to 0, the smaller the gap is. The Gini coefficient has been widely used in fields such as medicine, geography, and computing (Chen et al., 1982). The Gini coefficient decomposition model was put forward by Dagum C in 1997; this model can describe the spatial differences of the remote sensing research output as a whole and quantify differences within and between regions compared with the ordinary Gini coefficient model (Dagum, 1997). The total Gini coefficient calculation formula is as follows:

$$G = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{n_i}\sum_{h=1}^{n_j}\left|y_{ik} - y_{jh}\right|}{2n^2\bar{y}}, \tag{3}$$

where N is the number of continents and n is the number of countries/regions. n_i, n_j are the number of countries/regions in continents i and j, respectively; y_{ik} and y_{jh} are the output of remote sensing research in country/region k and country/region h in continents i and j, respectively; and $\bar{y}$ is the average output of remote sensing research.

According to the Gini coefficient decomposition model of Dagum C, the total Gini (G) can be decomposed as follows:

$$G = G_w + G_{nb} + G_t, \tag{4}$$

where G_w measures the contribution of differences in the number of remote sensing research within continents to the total Gini; G_{nb} measures the contribution of differences in the number of remote sensing research between continents to the total Gini; and G_t measures the contribution of the various intensity of the number of remote sensing research between continents to the total Gini. Among them, G_w, G_{nb}, and G_t are as follows:

$$G_w = \sum_{j=1}^{N} G_{jj} p_j s_j, \tag{5}$$

$$G_{nb} = \sum_{j=2}^{N}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right) D_{jh}, \tag{6}$$

$$G_{nb} = \sum_{j=2}^{N}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)\left(1 - D_{jh}\right), \tag{7}$$

where G_{jj} is the Gini coefficient within the continent j; G_{jh} is the Gini coefficient between continent j and continent h; D_{jh} is the relative influence of remote sensing research output between continents j and h; $p_j = n_j/n$ is the ratio of the number of countries/regions in the continent j to the number of countries/regions in all continents; $S_j = n_j\bar{Y}_j/n\bar{y}$, $j = 1, 2, \ldots, N$; $\bar{Y}_j$ is the average output of remote sensing research in the continent j; and D_{jh} is the relative influence of the output of research in remote sensing between continent j and continent h.

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji} - y_{jr}\right|}{2n_j^2\bar{Y}_j}, \tag{8}$$

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji} - y_{jr}\right|}{n_j n_h\left(\bar{Y}_j + \bar{Y}_h\right)}, \tag{9}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}}, \tag{10}$$

where y_{ji} is the output of remote sensing research from a country i on the continent j; $\bar{Y}_j$ is the average output of remote sensing research for all countries on the continent j; and n_j is the number of countries on the continent j; $p_j = n_j/n$ is the ratio of the number of countries/regions in the continent j to the number of countries/regions in all continents; d_{jh} is the mathematical expectation of the sum of samples satisfying $y_{jt} - y_{hr} > 0$ in continent j and continent h; p_{jh} is the mathematical expectation of the sum of samples satisfying $y_{hr} - y_{jt} > 0$ in continent h and continent j.

3.3 ESDA

ESDA is the application of exploratory data analysis (EDA) to spatial data analysis (SDA). It includes global spatial autocorrelation analysis and local spatial autocorrelation analysis. Different from global spatial autocorrelation describing the spatial aggregation degree of the research object in the whole research region (Griffith et al., 2003), local spatial autocorrelation describes the similarity between research objects, which can be used to measure the degree of local units obeying the whole (Flahaut et al., 2003; Jing et al., 2021). Generally, local spatial autocorrelation analysis can reveal the location of the research object that has local spatial autocorrelation when the global spatial autocorrelation is not significant. When the global spatial autocorrelation is significant, local spatial autocorrelation analysis can reveal the spatial heterogeneity of the study object.

3.3.1 Global spatial autocorrelation

In this study, the global $Moran's\,I$ was used to measure the global spatial autocorrelation of the remote sensing research output. A global $Moran's\,I$ value above 0 indicates a positive spatial correlation (i.e., spatial aggregation) in the research output, while a value below 0 indicates a negative spatial correlation (i.e., spatial dispersion). The research output in remote sensing is considered to have no spatial relevance when the global $Moran's\,I$ value is equal to 0. The global spatial autocorrelation formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(y_j - \bar{y})^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}, \tag{11}$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}), \tag{12}$$

where n indicates the number of countries/regions; y_i, y_j represent the research output in remote sensing in a country/region i and j, respectively; $\bar{y}$ is the average number of research in remote sensing and w_{ij} is the spatial weight between the ith country/region and the jth country/region. The value range is as follows:

TABLE 1 Classification of local spatial correlation.

Category	I	Z(I)
High–High	$0 < I \le 1$	$1.96 < Z(I) < +\infty$
Low–Low	$0 < I \le 1$	$-\infty < Z(I) < -1.96$
High–Low	$-1 \le I < 0$	$-\infty < Z(I) < -1.96$
Low–High	$-1 \le I < 0$	$1.96 < Z(I) < +\infty$

$$w_{ij} = \begin{cases} 1, & i \cap j \neq \varnothing \\ 0, & i \cap j = \varnothing \end{cases}. \tag{13}$$

3.3.2 Local spatial autocorrelation

Taking i as the country/region in the study area, the formula of the local $Moran's\,I$ index I_i of country/region i is as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2}\sum_{j=1}^{n} w_{ij}(x_j - \bar{x}). \tag{14}$$

The formula for the significance level of the local $Moran's\,I$ index I_i of country/region i is

$$Z(I_i) = \frac{I_i - E(I_i)}{\sqrt{\mathrm{VAR}(I_i)}}. \tag{15}$$

Under a certain significance level, the local spatial correlation can be classified into four types: High–High, Low–Low, High–Low, and Low–High by calculating the values with I and Z (I) (Table 1). Among them, both High–High and Low–Low indicate positive spatial correlation, implying large spatial similarity between neighboring countries/regions, i.e., spatial aggregation, while High–Low and Low–High indicate negative spatial correlation, implying large spatial differences between neighboring countries/regions, i.e., spatial dispersion.

4 Results

4.1 Overview

In this study, the national research production statistics are based on the country/region where the institutions are located, in which authors complete related research. In addition, many articles are finished under the international collaboration. In order to be consistent with existing related studies, we counted the collaborative articles for each involved country once. For example, if an article is completed by researchers from the United States, China, and the United Kingdom, this article will be counted for all three countries (Lin et al., 2016; Leung et al., 2017).

A total of 153 countries/regions published remote sensing studies during 2012–2021, 19 of which contributed only one

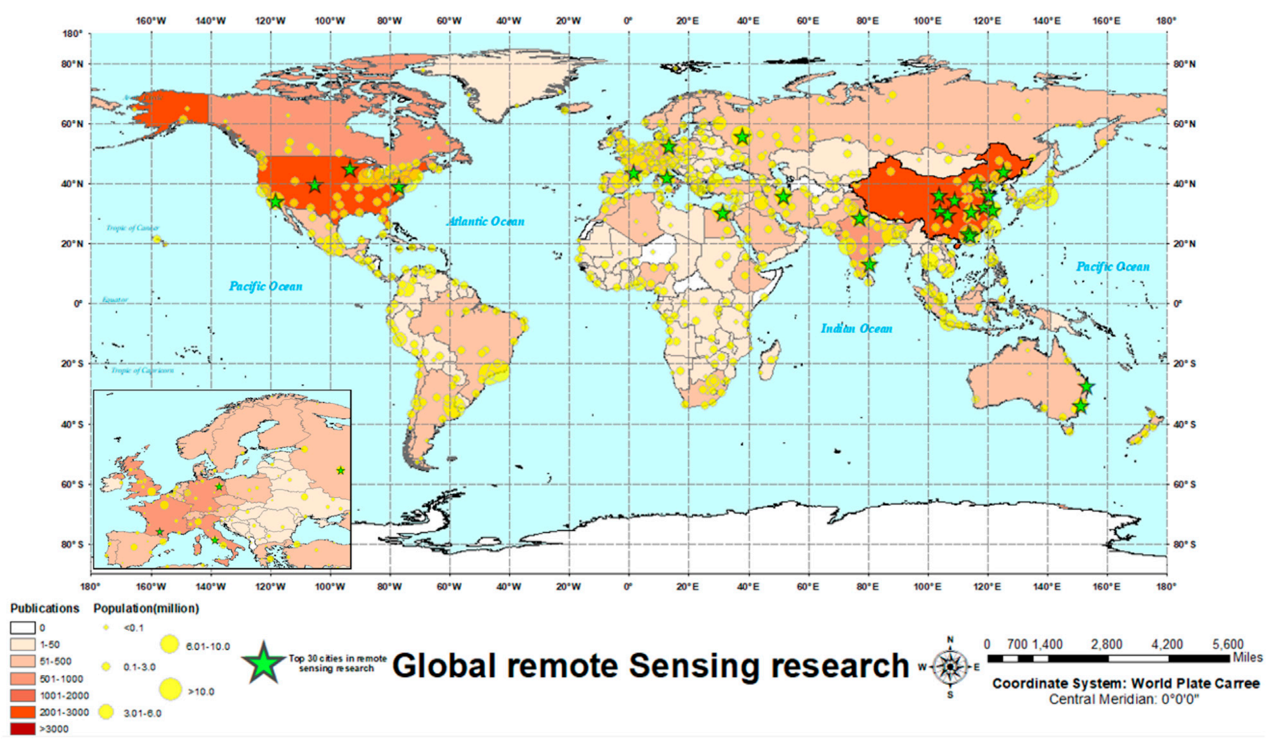

FIGURE 1
Geographic distribution of the global remote sensing research paper output.

(Figure 1). Figure 1 shows that the top 30 cities with high research output were those with large populations. The 10 most productive countries/regions contributed 68.78% of the total studies, with the United States and China being the two most active countries/regions in remote sensing research (Figure 1). China and the United States had the largest numbers of research publications, 5,389 and 2,649 research, respectively. Developed countries such as the United Kingdom, Italy, France, Canada, and Spain also had high output. Large emerging countries, including India (947), Brazil (331), Iran (310), and Egypt (260), have large populations or are large energy consumers. Articles from these countries mostly focused on society, the environment, and energy. To some extent, this indicates that the economic level plays a vital role in scientific input in remote sensing (Li et al., 2016; Lukac et al., 2016; Mikhaylov et al., 2021). Furthermore, for countries/regions with large populations, especially emerging developing countries/regions, new methods based on remote sensing technologies have been sought to solve social problems (such as traffic congestion, environmental pollution, etc.) caused by population growth or develop new technologies for energy surveys (for mineral exploration, etc.) to reduce costs and improve the efficiency of energy exploration (Duane et al., 2021; Chen et al., 2022; Wu et al., 2022).

4.2 Annual publication

Figure 2 describes the annual output of remote sensing research. In Figure 2, the total global citation score (TGCS) indicates the total citations of a remote sensing research by study in the whole database, representing the influence of that research on the academic community, while the total local citation score (TLCS) indicates the citations in the field of this study, which showcases its influence within the field. It can also be seen that 12,549 studies were produced in the field during 2012–2021. 2012 was the year with the lowest yield, with 709 published research, while 2021 had the highest yield, with the publication of 2,576 research. An average of 1,331.8 research was published per year, with an average of 2,105 citations per year (21,050 citations in total in research in the field). The total number of citations in the whole database reached 181,944, an average of 18,194.4 citations per year.

During 2012–2021, the first peaks of the TLCS and TGCS emerged in 2013. In 2013, the study *The detection of "hot regions" in the geography of science—A visualization approach by using density maps* and *Automatic landslide detection from remote-sensing imagery using a scene classification method based on BoVW and pLSA* had the highest TGCS and TLCS, respectively (Bornmann and

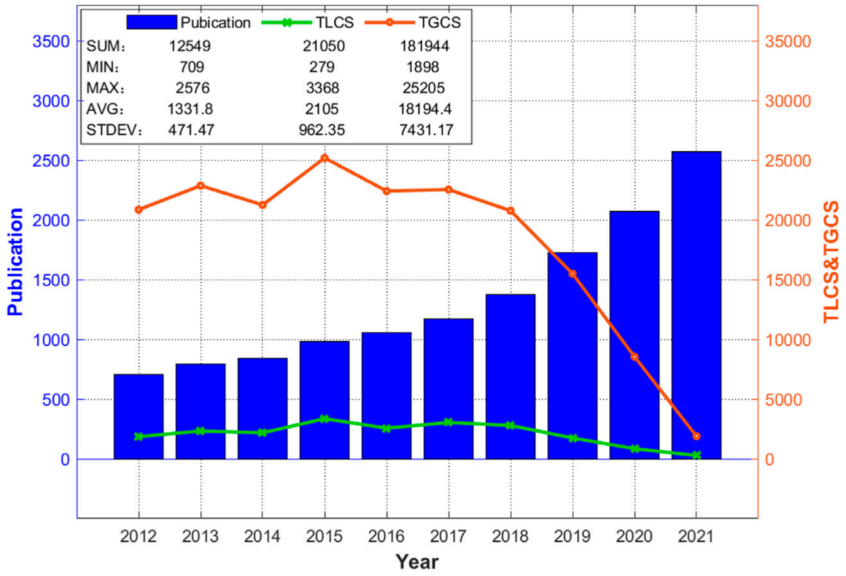

FIGURE 2
Temporal distribution of the output of remote sensing research from 2012 to 2021.

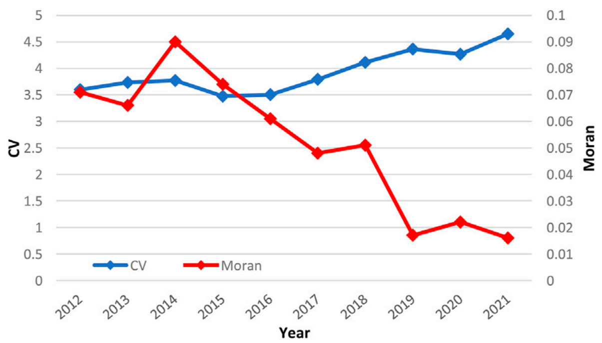

FIGURE 3
Line graph of the annual index change of remote sensing research output.

TABLE 2 Annual index of remote sensing research output.

Year	STDEV	CV	Moran
2012	24.1585	3.5976	0.071
2013	29.0000	3.7332	0.066
2014	31.1722	3.7716	0.090
2015	34.5797	3.4741	0.074
2016	37.1906	3.5033	0.061
2017	43.7571	3.7930	0.048
2018	57.4446	4.1129	0.051
2019	79.0978	4.3638	0.017
2020	91.7205	4.2680	0.022
2021	82.1665	4.6503	0.016

Waltman, 2011; Cheng et al., 2013). After a temporary rebound in 2014, the TGCS and TLCS reached the peak of their research duration in 2015 simultaneously, demonstrating that the academic achievements of this year attracted high attention from both the respective fields and the whole academic community (Figure 2). *Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery* was the research with the highest TGCS and TLCS during 2012–2021 (Hu et al., 2015). After 2016, the TLCS and TGCS continuously declined; however, remote sensing research output displayed an upward trend. This result does not suggest that the research conducted after 2016 is not important or that the academic community has lost interest in remote sensing. It is more like a reflection of the delayed citation window effect (O'Leary et al., 2015; Chi, 2016; Gonzalez and Gonzalez, 2016; Hu et al., 2019), which means that it takes time from publication to citation (Campanario, 2011; Chi, 2016). In general, the citation of research is directly related to its publication time. The earlier the article is published, the more times it will be cited (Leung et al., 2017; Hu et al., 2019). Conversely, the research output in remote sensing has been increasing since 2016, which indicates that research in remote sensing has attracted ongoing attention from both its own field and the global community (Figure 2) (Weng, 2009; Zhuang et al., 2013).

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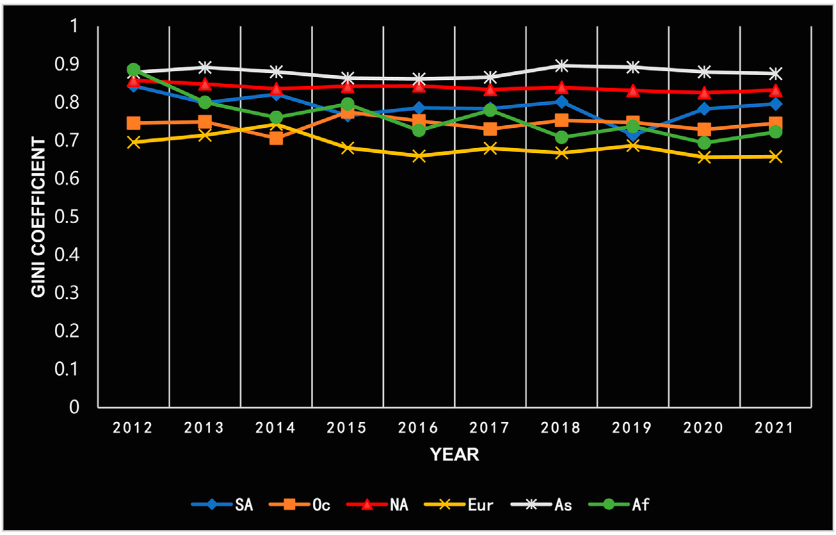
TABLE 3 Gini coefficient and decomposition results of the output of remote sensing research.

		Year									
		2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Gini		0.8741	0.8733	0.8741	0.8503	0.8417	0.8495	0.8634	0.8588	0.8469	0.8519
Gini coefficient of intra-continental(G_w)	SA	0.8444	0.8000	0.8222	0.7667	0.7863	0.7846	0.8024	0.7152	0.7839	0.7969
	Oc	0.7467	0.7500	0.7070	0.7758	0.7524	0.7314	0.7536	0.7481	0.7297	0.7463
	NA	0.8587	0.8490	0.8366	0.8433	0.8440	0.8347	0.8402	0.8321	0.8263	0.8328
	Eur	0.6962	0.7150	0.7433	0.6815	0.6603	0.6805	0.6684	0.6875	0.6571	0.6588
	As	0.8796	0.8926	0.8812	0.8647	0.8623	0.8669	0.8972	0.8933	0.8809	0.8762
	Af	0.8865	0.8010	0.7615	0.7967	0.7273	0.7805	0.7093	0.7378	0.6946	0.7234
Gini coefficient of inter-continental (G_{nb})	SA–Oc	0.8737	0.8581	0.8260	0.8504	0.8521	0.8038	0.8672	0.8144	0.8308	0.8196
	SA–NA	0.9677	0.9632	0.9396	0.9538	0.9551	0.9444	0.9534	0.9239	0.9298	0.9265
	SA–Eur	0.8597	0.8468	0.8378	0.8199	0.8215	0.8237	0.8264	0.7884	0.7956	0.7858
	SA–As	0.9112	0.9090	0.8924	0.8796	0.8884	0.8903	0.9122	0.8860	0.9023	0.9010
	SA–Af	0.8956	0.8250	0.8708	0.8129	0.7884	0.8143	0.8062	0.7635	0.7799	0.8049
	Oc–NA	0.9118	0.9041	0.8755	0.9122	0.8937	0.9070	0.8768	0.8696	0.8553	0.8659
	Oc–Eur	0.7480	0.7660	0.7432	0.7749	0.7448	0.7499	0.7367	0.7518	0.7205	0.7330
	Oc–As	0.8554	0.8724	0.8480	0.8695	0.8519	0.8532	0.8743	0.8758	0.8568	0.8693
	Oc–Af	0.9438	0.9110	0.9320	0.9049	0.8797	0.8608	0.9091	0.8818	0.8688	0.8762
	NA–Eur	0.8915	0.8825	0.8741	0.8600	0.8598	0.8574	0.8632	0.8554	0.8383	0.8478
	NA–As	0.9198	0.9132	0.9052	0.9042	0.8993	0.8991	0.9125	0.9029	0.8892	0.8989
	NA–Af	0.9871	0.9802	0.9798	0.9760	0.9725	0.9688	0.9743	0.9567	0.9522	0.9615
	Eur–As	0.8194	0.8390	0.8442	0.8085	0.7985	0.8098	0.8344	0.8412	0.8192	0.8243
	Eur–Af	0.9341	0.8994	0.9297	0.8927	0.8641	0.8724	0.8776	0.8616	0.8365	0.8369
	As–Af	0.9541	0.9376	0.9414	0.9214	0.9095	0.9183	0.9339	0.9250	0.9223	0.9249

Notes: SA: South America; Oc: Oceania; NA: North America; Eur: Europe; As: Asian; Af: Africa.



(Notes.: SA: South America; Oc: Oceania; NA: North America; Eur: Europe; As: Asian; Af: Afric)

FIGURE 4
Evolution of the intracontinental variation in the output of remote sensing research. (Notes.: SA: South America; Oc: Oceania; NA: North America; Eur: Europe; As: Asian; Af: Africa).

4.3 Spatial characteristics

The standard deviation of the research output in remote sensing has been on the rise from 2012 to 2021, and that in 2021 was 82.1665, which was 240.11% higher than that in 2012. In addition, its coefficient variation has been increasing significantly since 2012 (Figure 3), and it was 4.6503, 29.26% higher than that of 2012 (Table 2). This indicates a significant dispersion of research output in remote sensing during the time period, especially after 2017. One major reason is that the number of countries/regions involved in remote sensing increased yearly, and the annual research output of the original high-producing countries/regions increased quickly. In the initial stage, the publication of newly involved countries/regions is usually less than that of developed countries/regions, thus leading to an increase in the values of the standard deviation and coefficient of variation year by year. To a certain extent, this result reflects that remote sensing has attracted the attention of scholars in an increasing number of countries/regions (Zhuang et al., 2013; Schmitt et al., 2017; Morales-Barquero et al., 2019). However, it is worth noting that this phenomenon may lead to a decrease in the spatial aggregation of remote sensing studies (Zhuang et al., 2013; Ma et al., 2019b; Jin and Li, 2019; Xu and Yang, 2020).

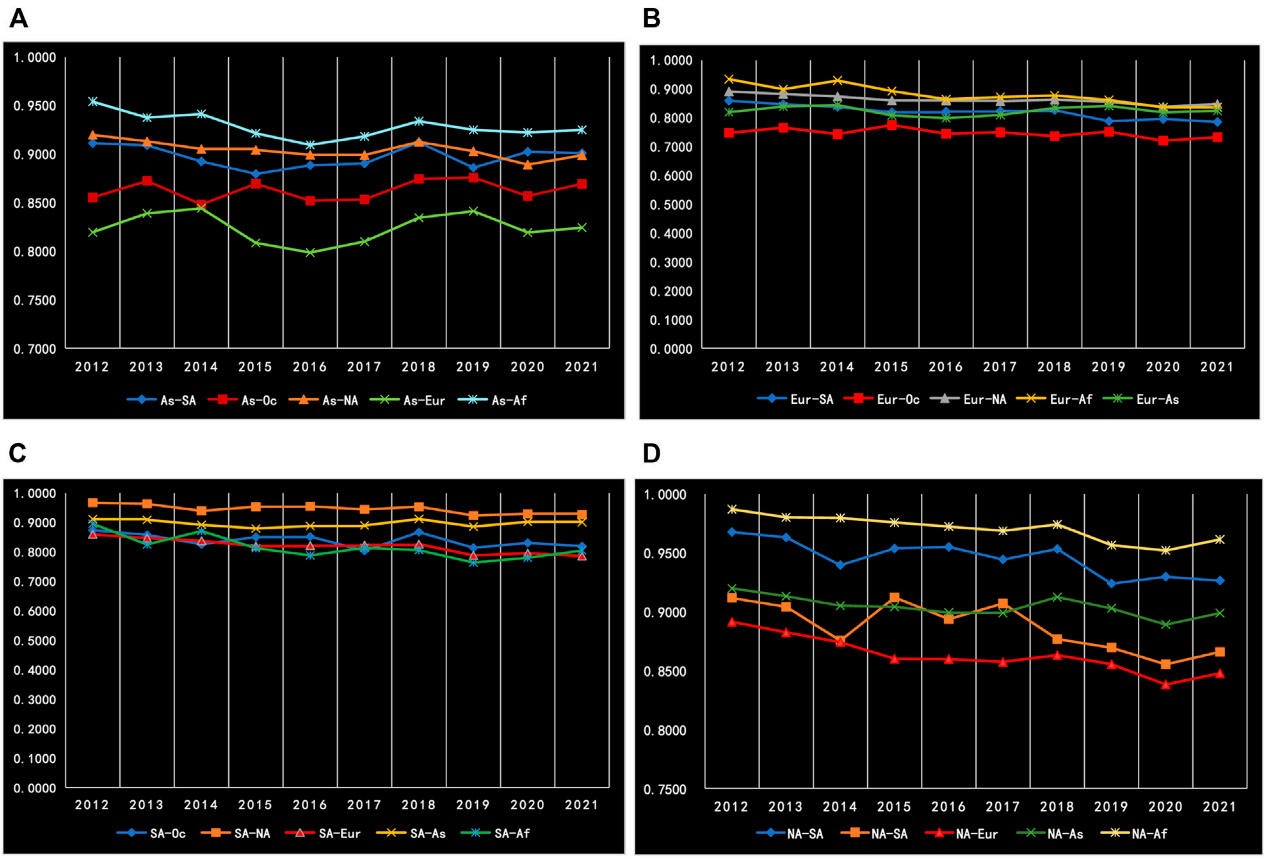
During 2012–2021, the Moran index was above 0. There was a positive spatial correlation in the remote sensing research output, indicating spatial clustering in the sensing field, which is consistent with the conclusion of Figure 1. In addition, from 2012 to 2014, the Moran index increased and then decreased, which suggests the same trend of remote sensing research output agglomeration (Figure 3). After 2015, the Moran index continued to decline and fell to 0.016 in 2021, meaning that the research output was still spatially aggregated to a significantly lower degree than in the last 3 years. One important reason is that collaborative research before 2018 was mostly among countries/regions that are geographically close to each other or among institutions within countries/regions (Fuentes, 2006; Weng, 2012; Zhuang et al., 2013). After 2019, it became more international, involving more countries/regions and regions (Ma et al., 2019b; Morales-Barquero et al., 2019; Wu et al., 2022).

4.4 Spatial evolution

4.4.1 Regional differences

Based on the continental division of geography (Asia, Europe, Oceania, Africa, North America, and South America) and the Dagum C algorithm, this study calculated the Gini coefficients of six continents to analyze the intra and intercontinental differences in research output in remote sensing.

The Gini coefficient of the remote sensing research output decreased, and the smaller indicator shows the research convergence. In addition, the regional imbalance decreased (Table 3). As shown in Figure 4, the largest intracontinental disparity in remote sensing research output during 2012–2021 was observed in Asia (G_w was the largest), while Europe showed the smallest intracontinental disparity (G_w was the smallest), and North



(Notes.: SA: South America; Oc: Oceania; NA: North America; Eur: Europe; As: Asian; Af: Africa)

FIGURE 5
(A–D) respectively show the evolution of intercontinental differences in remote sensing research output between Asia, Europe, South America, and North America and other continents. (Notes.: SA: South America; Oc: Oceania; NA: North America; Eur: Europe; As: Asian; Af: Africa).

America was relatively stable, fluctuating at approximately 0.83. In Africa, the Gini coefficient of intracontinental differences decreased dramatically, indicating that the intracontinental differences in the research output on the continent have significantly declined.

Asia, the continent with the largest intracontinental disparity of research output in remote sensing fields, had the largest intercontinental Gini coefficient with Africa and the smallest with Europe (Figure 5A); Europe, the continent with the smallest intracontinental disparity, also had the largest with Africa and the smallest with Oceania (Figure 5B). In the Americas, South America had the largest intercontinental Gini coefficient with North America and the smallest with Africa (Figure 5C); North America had the largest with Africa and the smallest with Europe (Figure 5D). Overall, the intercontinental disparity is dropping. Taking 2012 as the base period, most of the six intercontinental Gini coefficients declined, with Europe-Africa decreasing the most (by 10.4%) and South America-Asia the least (by 1.11%). The regional differences in research output decreased.

4.4.2 Spatial patterns

Figure 6 shows the 30 countries/regions with the most active research output in remote sensing during 2012–2021. As shown in Figure 6, the number of involved Asian countries/regions increased from 6 to 10 in 2012, while the number of involved European countries/regions decreased from 16 to 12. In 2012, the United States was the largest country/region in terms of research output, with China, India, Germany, and the United Kingdom ranking 2–5. China became the country/region with the largest scientific research work output during 2013–2021, and India moved up to the top three after 2018.

The changes in quadrants in Figure 7 reflect the local spatial evolutionary characteristics of the output of research work related to remote sensing. Table 4 presents the countries/regions included in

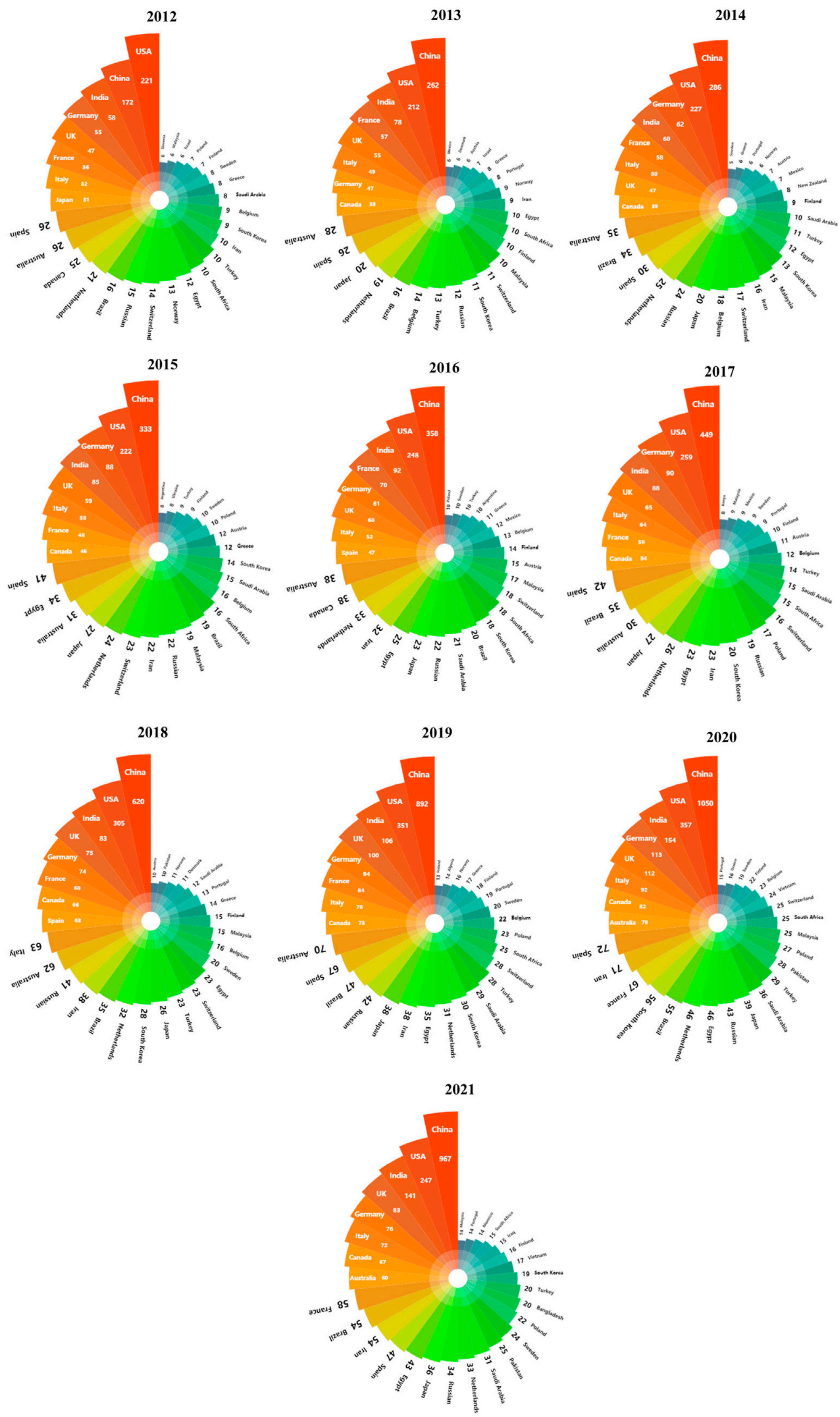


FIGURE 6
Top 30 countries with the most active output of remote sensing research.

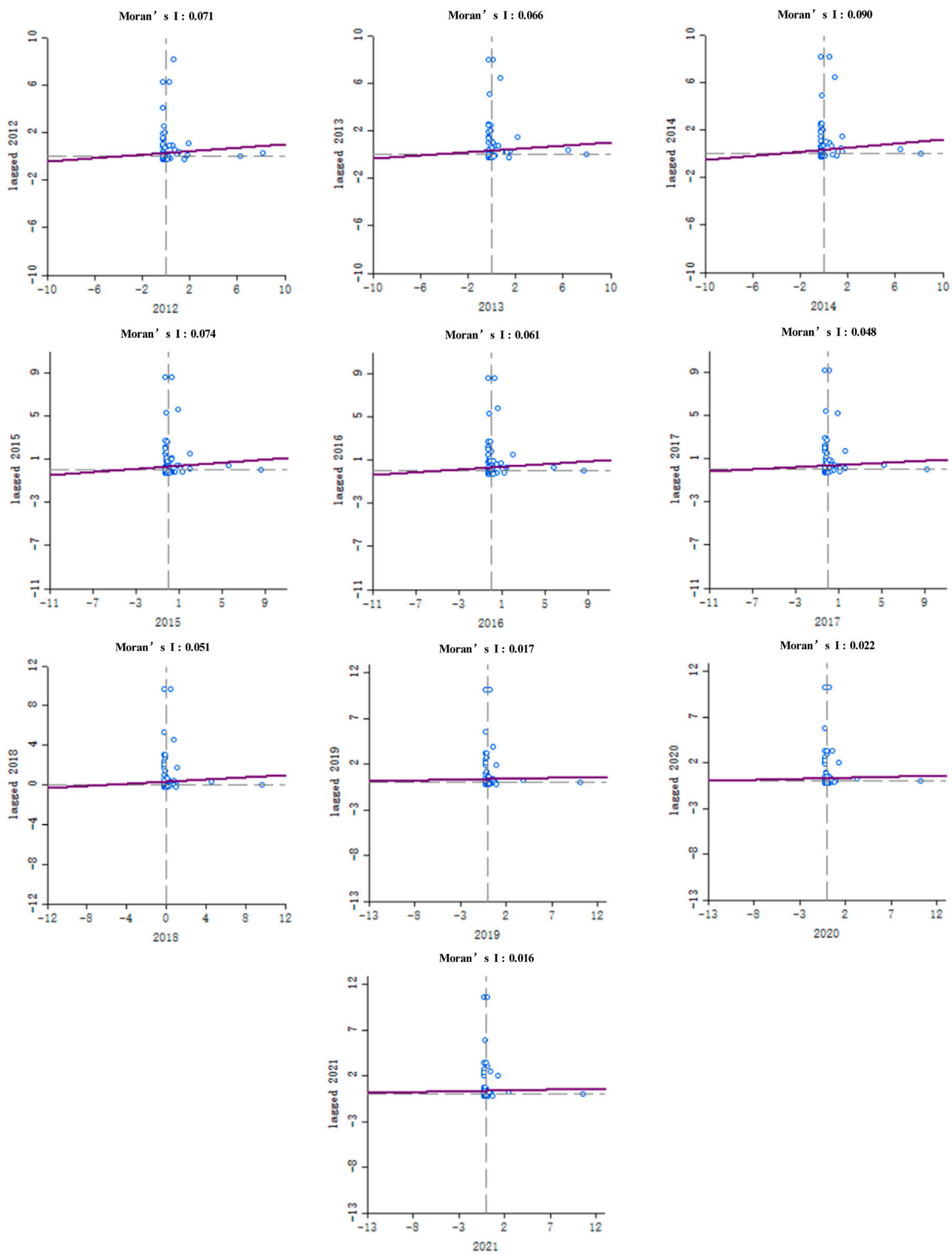


FIGURE 7
Scatterplot of the Moran index of the output of remote sensing research.

TABLE 4 Corresponding countries/regions of the Moran scatterplot for the output of remote sensing research.

	Year				
	2012	**2013**	**2014**	**2015**	**2016**
High–High	Canada Netherlands Russian	Canada India Russian Spain	Canada India Netherlands Russian Spain	Canada, India, Netherlands, and Russian	Canada, India, Russian, and Spain
Low–High	Afghanistan, Bangladesh, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Bangladesh, Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Denmark, French Guiana Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Bangladesh, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam
Low–Low	Guinea, Mali, Democratic Republic of the Congo, and Zambia	Burkina Faso Cote D'ivoire, Guinea, and Tanzania	Burkina Faso Cote D'ivoire, Guinea, Mali, Tanzania, and Democratic Republic of the Congo	Angola Congo Cote D'ivoire, Guinea, Nigeria, Tanzania, Democratic Republic of the Congo, and Zambia	Angola Burkina Faso Cote D'ivoire, Ghana, Guinea, Liberia Mali, Tanzania, Democratic Republic of the Congo, and Zambia
High–Low	United Kingdom and South Africa	United Kingdom			

	Year				
	2017	**2018**	**2019**	**2020**	**2021**
High–High	Canada, India, Netherlands, and Russian	Canada, India, Netherlands, and Russian	Canada, India, Netherlands, and Russian	Canada, India, Pakistan, and Russian	Canada, India, Pakistan, and Russian
Low–High	Afghanistan Denmark Ireland Kazakhstan Kyrgyzstan Laos Luxembourg Mexico Mongolia Myanmar Nepal Pakistan Viet Nam	Afghanistan, Bangladesh, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Laos, Luxembourg, Mexico, Mongolia, Myanmar, Nepal, Pakistan, and Viet Nam	Afghanistan, Bangladesh, Denmark, Ireland, Kazakhstan, Kyrgyzstan, Laos, Mexico, Mongolia, Myanmar, Nepal, Luxembourg, and Viet Nam	Afghanistan, Denmark, Ireland, Kazakhstan, Bangladesh, Kyrgyzstan, Laos, Mexico, Mongolia, Myanmar, Nepal, and Viet Nam
Low–Low	Angola, Burkina Faso, Guinea, Liberia Mali, Tanzania, Democratic Republic of the Congo, and Zambia	Angola, Congo, Guinea, Nigeria Tanzania, Democratic Republic of the Congo, and Zambia	Angola, Tanzania, Democratic Republic of the Congo, and Zambia	Angola, Burkina Faso, Congo, Cote D'ivoire, Guinea, Senegal Nigeria Tanzania, Democratic Republic of the Congo, and Zambia	Angola, Burkina Faso, Cote D'ivoire, Ghana, Guinea, Liberia Mali, Senegal, Tanzania, and Democratic Republic of the Congo
High–Low					

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TABLE 5 Top10 articles of remote sensing with the highest TLCS.

No.	Article	TLCS	TGCS	References
1.	Remote Sensing Image Scene Classification: Benchmark and State of the Art	258	616	Cheng et al. (2017)
2.	Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Images	226	775	Cheng et al. (2016)
3.	Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery	198	632	Hu et al. (2015)
4.	When Deep Learning Meets Metric Learning: Remote Sensing Image Scene Classification via Learning Discriminative CNNs	157	461	Cheng et al. (2018)
5.	Deep Learning for Remote Sensing Data A technical tutorial on the state of the art	143	863	Zhang et al. (2016)
6.	Towards better exploiting convolutional neural networks for remote sensing scene classification	139	433	Nogueira et al. (2016)
7.	Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources	139	816	Zhu et al. (2017)
8.	Deep Learning Based Feature Selection for Remote Sensing Scene Classification	107	322	Zou et al. (2015)
9.	Object Detection in Optical Remote Sensing Images Based on Weakly Supervised Learning and High-Level Feature Learning	100	447	Han et al. (2014)
10.	Accurate Object Localization in Remote Sensing Images Based on Convolutional Neural Networks	99	222	Long et al. (2017)

each quadrant in Figure 5. As seen from Table 4, a total of 6 countries/regions entered the high–high cluster from 2012 to 2021, with low–high, low–low, and high–low comprising 16, 12, and 2 countries, respectively. Moreover, two countries/regions (Canada and Russia) are in the High–High cluster, indicating that the outputs of research work related to remote sensing in these countries/regions and their neighboring countries/regions were at a relatively high level and stable. In addition, 9 countries/regions are in the low–high category. In general, the countries/regions located in each quadrant were relatively stable in the research period, and only a few countries/regions underwent quadrant location changes. For example, Pakistan moved from the second quadrant (low–high) to the first quadrant (high–high), which demonstrates the output of scientific research work in Pakistan and its neighboring countries/regions or regions improved.

5 Discussion

According to the previous analysis, the gap in the research work output regarding global remote sensing between the different continents decreased, and the spatial aggregation was obviously reduced. The top 10 countries/regions with the largest amount of published research were not the top 10 countries/regions with the largest gross domestic product (GDP). Similarly, the ranking of GDP was not consistent with the research output of the country/region. Meanwhile, almost all the top 30 cities with the largest research work output were among the top 30 in terms of urban populations; however, some cities with large populations like Tokyo and So Paulo fail to make top -30 listed countries with their research output. To some extent, although not decisively, regional economic development and the population have significant impacts on the output of research work in relevant fields of remote sensing (Li et al., 2016; Lukac et al., 2016; Ma et al., 2019a; Ma et al., 2019b).

During the past decade, the output of research work on remote sensing has increased sharply. With more countries/regions concerned about remote sensing and the wider geographic distribution of the nations, the most active countries/regions in the remote sensing research involved the main developed countries/regions as well as emerging developing countries/regions. Tables 5 and 6 show remote sensing research published from 2012 to 2021 with the top 10 TLCS and TGCS values. Most of the study with high TLCS and TGCS was published after 2016, representing the most cutting-edge studies on remote sensing. During this period, studies with a higher TGCS were published in 2013. Interestingly, the ranking of TLCS in Table 6 was not identical to that of TGCS. Generally, published research will be cited by work in this field first, and then cited by studies in other fields after a period of time. During this period, two situations may occur: first, the method or idea proposed in this study may be refuted or optimized by other research in this field

TABLE 6 Top 10 articles of remote sensing with the highest TGCS.

No.	Article	TLCS	TGCS	References
1.	Hyperspectral Remote Sensing Data Analysis and Future Challenges	40	908	Bioucas-Dias et al. (2013)
2.	Deep Learning for Remote Sensing Data A technical tutorial on the state of the art	143	863	Zhang et al. (2016)
3.	Deep Learning in Remote Sensing: A Comprehensive Review and List of Resources	139	816	Zhu et al. (2017)
4.	Learning Rotation-Invariant Convolutional Neural Networks for Object Detection in VHR Optical Remote Sensing Images	226	775	Cheng et al. (2016)
5.	Twenty 5 years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps	50	705	Mulla, (2013)
6.	Transferring Deep Convolutional Neural Networks for the Scene Classification of High-Resolution Remote Sensing Imagery	198	632	Hu et al. (2015)
7.	Remote Sensing Image Scene Classification: Benchmark and State of the Art	258	616	Cheng et al. (2017)
8.	Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends	62	601	Weng, (2012)
9.	Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data	58	493	Kussul et al. (2017)
10.	Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification	90	465	Maggiori et al. (2017)

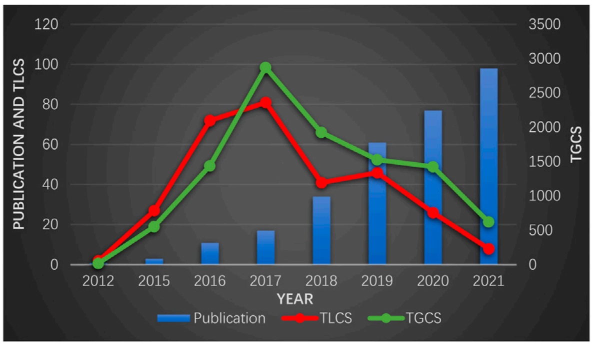

FIGURE 8
Annual yield of remote sensing research to deep learning.

but is being borrowed and used by other fields; therefore, this study gets a low TLCS ranking and a high TGCS ranking; second, the method or idea proposed in this study is only applicable to this field, so it is ranked high in TLCS but low in TGCS (Hu et al., 2019; Jin and Li, 2019).

As shown in Tables 5 and 6, there were five study associated with deep learning and focused on target detection, scene understanding, and autonomous exploration. Meanwhile, the number of remote sensing research related to in-depth learning increased from 3 in 2015 (accounting for 0.3% of the total number of research) to 98 in 2021 (5.43%), showing a significant upward trend (Figure 8). In recent years, with the soaring development of computer vision, such as image classification, target identification, and semantic segmentation, deep learning has been widely applied to remote sensing and has become an important innovation driver for remote sensing research (Zhang et al., 2016; Leung et al., 2017; Kozlowski et al., 2020).

The continental imbalance in the output of remote sensing research work decreased. The continental gap in output in Asia was the largest, while the gap in Europe was the smallest (Table 3; Figure 4). In Asia, there were nations with advanced academic institutions, talented scientific researchers, and large research work output as well as nations with unfavorable research conditions, few scientific researchers, and small study output (Klein et al., 2014; de Beurs et al., 2015; Vadrevu et al., 2019). Thus, the gap in research work output in Asia was larger than that in Europe (Goga et al., 2019; Chen et al., 2020; Mikhaylov et al., 2021). Moreover, the continental gap in Africa has obviously narrowed due to the increasing investment in scientific research in the current decade (Khechba et al., 2021; Mngadi et al., 2022; Sebola, 2022). Regarding the continental gap between Asia and other continents, the gap between Asia and Africa was the largest, and the gap between Asia and Europe was the smallest (Figure 5A), showing that the gap between the two continents with high research output was not large. The gaps between Europe and other continents were all smaller than those between Asia and other continents. In contrast, the gap between Europe and Africa was the largest (Figure 5B), suggesting a large imbalance between Africa and other continents with high research output, such as Asia and Europe.

With the development of communication technology, the cost of cross-regional cooperation decreased, thus promoting international cooperation (Figure 5). Recently, with the help of artificial intelligence, deep learning, and blockchain technologies, remote sensing has been widely and deeply applied to national defense, the economy, and people's daily lives (Zhu et al., 2017; Kocaman and Ozdemir, 2020; Jung et al., 2021). With an increasing number of countries/regions paying attention to remote sensing, some with lower output will become high-output countries/regions, and some less developed countries/regions will no longer have low output, so the spatial aggregation of the professional research work on remote sensing will decrease.

Despite the above discoveries, due to the limitations of the data, there is an inevitable deficiency in the methodological universality of this exploratory research. Initially, because of data availability and the heterogeneity of the different databases, data from the WoS core database were used in this study. Although the data have high authority, its lack of comprehensiveness cannot be ignored. During the over 10-year research, the name of some institutions may have changed or even become defunct. Secondly, the same university, organization, and institution might be in different cities, so we decided to analyze the research output at the national level. Lastly, the weight impacts and author priority in the cooperation were not taken into account in the research output analyses. In future studies, we will improve the availability and scientific rigor of the results by considering the above limitations.

6 Conclusion

Based on 13,057 research articles included in the WoS from 2012–2021, this study probed the spatiotemporal distribution and evolutionary characteristics of research work output in remote sensing by utilizing scientometric and exploratory spatial analysis. The conclusions are as follows:

Over the last decade, the output of remote sensing research has increased significantly, and its spatial distribution presents a significant dispersion trend. Countries/regions actively participating in remote sensing research included both developed and emerging developing countries/regions, among which the United States and China were the most active. Although the regional economic level and population size play important roles in the remote sensing research work output, neither factor is a determinant. Nearly half of the top ten studies with the highest TGCS and TLCS values were related to deep learning, suggesting that deep learning technology will be one of the most important drivers of innovation in future remote sensing application models. The regional imbalance of the research work output in remote sensing generally dwindled. Although both Asia and Europe had the largest remote sensing research work output, the intracontinental disparity in Asia was the largest, and that in Europe was the smallest, which is related to uneven regional development. The continuous development of telecommunication and other technologies reduces the cost of cross-regional cooperation, and international cooperation in remote sensing has become more frequent. As a result, massive incorporation can bring new technologies and methods. Moreover, remote sensing technology has been widely applied to various fields, such as national defense and economics. More national attention has been given to remote sensing, resulting in mitigation of the clustering of research work output in remote sensing fields.

The results of this study can help countries/regions and institutions understand the overall situation of research output and the continental research gaps in remote sensing as well as improve understanding of the evolution trend of research output. By exploring the essential features of national/regional gaps, the results also serve as important sources of fundamental data and decision-making references for the spatial allocation optimization of scientific and technological resources and regional gap reduction. However, a few limitations and shortcomings should be noted, and future efforts are needed. 1) Although the adopted data source is sufficiently authoritative, it is relatively simplistic and not comprehensive. 2) Due to various reasons, the research work output in remote sensing fields was only analyzed at the national/regional scale, leading to a lack of universality of the conclusions. 3) The absence of weight calculation and priority analysis of institutional importance also affects the rigor of the results.

Data availability statement

Publicly available datasets were analyzed in this study. These data can be found at: Web of Science.

Author contributions

Conceptualization: YL, XK, and LX; software: FS and KW; visualization: YL and SW; writing—original draft preparation: YL and LX; and review and editing: SW, FS, and XK. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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