

A Bibliometric Analysis of Land Degradation and Desertification Monitoring Based on the Scopus Database (2021–2025)

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DOI: <https://doi.org/10.52939/ijg.v22i8.5142>

Abstract

Land degradation and desertification threaten ecological balance, agricultural productivity, and human well-being, particularly in arid and semi-arid zones. This study presents a bibliometric analysis of global research on land degradation and desertification monitoring using remote sensing and geographic information systems (GIS) for the period 2021–2025, based on the Scopus database. A total of 655 peer-reviewed articles were retrieved and analyzed with the Bibliometric package in R to examine publication trends, leading journals, productive authors, institutions, contributing countries, collaboration patterns, and thematic structure. The results show an overall upward trend in scientific output, especially after 2022, alongside the rapid integration of machine learning, cloud computing, and advanced satellite data into monitoring workflows; remote sensing, land degradation, and GIS were the most frequent keywords. Output and citations were highly concentrated in a few countries, led by China, and the institutional collaboration network displayed a core-periphery structure in which international cooperation was unevenly distributed. A complementary analysis indicated that severely affected dryland regions, especially Central Asia, remain under-represented in the international literature. The study also identifies persistent challenges, including unequal research capacity across regions and the limited field-based validation of remote-sensing assessments. By mapping the most recent research landscape and situating Central Asia within it, this work provides an updated, technology-focused reference point that complements earlier regional reviews and highlights priorities for future, more inclusive monitoring research.

Keywords: Deep Learning, Desertification, GIS, Land Degradation, Machine Learning, Remote Sensing

1. Introduction

1.1 Background and Significance

All continents except Antarctica are experiencing desertification, which has an impact on millions of people's livelihoods, including a sizable section of the impoverished in arid regions [1]. The degradation of land occurring in arid, semi-arid, and dry semi-humid zones due to various human interventions is referred to as desertification. Desertification results in the transformation of productive agricultural and grazing lands into desert lands, thus reducing the biological productivity of these lands [2]. Productive land is important for human beings. However, human intervention and climate change are leading to desertification and the

resultant degradation of productive lands. Desertification is one of the greatest environmental problems, affecting approximately 25% of the Earth's surface and one-fifth of its population [3]. The traditional theories of desertification indicate that this process is a transition from one stable ecosystem state to another state in bistable systems [4].

Desertification is now regarded as a land-system crisis with multiple dimensions [5] and [6]. It enhances poverty, hunger, biodiversity loss, water shortages, and instability in the livelihoods of dryland communities that depend on fragile ecosystem functions. According to recent review

articles, land degradation causes soil degradation and impairs the provision of ecosystem services, including the regulation of water and climate [6] and [7]. It also lowers the productivity of agricultural land, which in turn increases social vulnerability and reduces resilience to climate change. Furthermore, the factors causing desertification are very complex and include both variability in climatic conditions as well as anthropogenic factors like unsustainable use of the land, resource exploitation, and poor land management [8] and [9]. Often, these factors interact in complex ways, causing acceleration of the degradation processes, which makes them difficult to mitigate and restore [10] and [11]. Due to the increasingly serious nature of the problem worldwide, there is an ever-increasing demand for land monitoring using modern tools and techniques such as remote sensing [12] [13] and [14].

1.2 Socioeconomic and Environmental Impacts of Land Degradation

The problem is not only biophysical but also socioeconomic, because degraded land constrains rural livelihoods, deepens inequality, and can contribute to migration pressures and broader insecurity in environmentally stressed regions. For this reason, the literature increasingly argues that effective responses to desertification must move beyond short-term remediation [5]. Instead, they should adopt coordinated, long-term strategies centred on land restoration, continuous conservation and rehabilitation, and the sustainable management of land and water resources. Such an integrated approach is now viewed as essential for protecting ecosystem services, strengthening food systems, and supporting sustainable development in dryland environments [15]. Around the world, land is rapidly deteriorating. Healthy land resources and thriving ecosystems are necessary to ensure food security for the world's expanding population. However, global soil erosion is occurring up to 100 times faster than natural replenishment due to our current agricultural practices. Almost 953 million hectares of productive land worldwide are limited in their production by the high concentration of salts in the root zone soil. The world lost at least 100 million hectares of productive and healthy land annually between 2015 and 2019 [16]. A range of problems confronts global drylands within this millennium, which require a lot of management, scientific, and policy considerations to solve. Ecosystem functions and the systems of livelihood of the human beings living within such ecosystems could be enhanced through solutions to the challenges posed by matters of poverty, biodiversity

loss, soil erosion, and the culture of about 2.5 billion people. Such solutions have been illustrated through progress made in relation to drylands development, sustainability, and global change science. The Drylands Development Paradigm enables the tackling of complexities surrounding desertification and development in the drylands through understanding key elements that determine the success of the management and policy communities. This concept is based on a growing body of management and policy tools [17].

1.3 Remote Sensing and GIS for Monitoring Land Degradation

Taking into account the above-listed problems, remote sensing has a unique potential for the assessment and monitoring of desertification in various scales of space and time [18]. Besides, according to the requirements of the Sustainable Development Goals, it is necessary to enhance national capacities for conducting quantitative assessments and mapping their degraded lands in order to halt and reverse the trend towards land degradation. Moreover, Earth observations can serve to supplement and enhance official national data sources [19]. Earth observation technologies have been developed greatly since the 1960s, providing innovative approaches for the extraction of necessary information and unique datasets. This development had a huge impact on the field of land management, agriculture, and the environment, providing important insights for sustainable decision-making [20]. Further, the Normalized Difference Vegetation Index, invented in the 1980s, became a key tool for monitoring the process of desertification and is considered a vital biophysical indicator reflecting the state of vegetation [21]. Moreover, it will be useful for achieving the objectives of Land Degradation Neutrality outlined by the UNCCD through comparing the years for determining the reasons for degradation [22].

1.4 Research Objective

The main objective of this study is to conduct a comprehensive bibliometric analysis of scientific publications on land degradation and desertification monitoring using remote sensing and GIS from 2021 to 2025, based on data retrieved from the Scopus database. The study aims to identify publication trends, leading journals, influential authors, productive institutions, contributing countries, collaboration patterns, and emerging thematic areas within this research field. Though scientific attention towards land degradation and desertification has witnessed a sharp rise in recent years, owing to advancements in the use of various

methods such as remote sensing, GIS, machine learning techniques, cloud computing technologies, and satellite-based monitoring systems, the need still exists for conducting a systematic bibliometric study to identify emerging trends in the global research arena regarding this phenomenon. Most of the literature related to land degradation and desertification focuses on either case study analyses or methodological approaches, thereby limiting an overall understanding of research evolution. Specifically, the paper [23] examined Scopus-listed English language studies on the topic of land degradation in Central Asia in the years between 2000 and 2020, that is, only one region at an earlier time point. The current study, however, maps the worldwide literature regarding the years 2021 to 2025, focusing on the topic of remote sensing and GIS-based monitoring as well as the new technologies used since 2020 such as machine learning, cloud computing, and high-resolution satellites, using full-scale science mapping through Bibliometric (keyword co-occurrences, collaboration networks among authors and institutions, and h-, g-, and m-indices). Central Asia is also viewed here as an example of underrepresentation within the larger framework of the worldwide literature, offering another perspective on the matter.

It should be noted that the principal contribution of this study lies not in the bibliometric technique itself science mapping through Bibliometric is now a well-established and widely used approach but in the updated 2021–2025 time window, which captures the recent, technology-driven phase of the field following the widespread adoption of cloud computing and machine learning in monitoring workflows, and in the explicit positioning of Central Asia within this global landscape. The five-year window was chosen deliberately to extend the record established by [23], who covered 2000–2020; a longer retrospective window here would dilute the study's focus on this most recent and rapidly evolving period of methodological development. Hence, this research attempts to fill the void by reviewing the current literature and identifying the patterns, evolution, and development of the monitoring of land degradation and desertification research. Moreover, the focus of this review is on the depiction of the vulnerable regions of drylands, particularly Central Asia, where the problem of land degradation is serious but might be underestimated in scientific publications globally.

To achieve this objective, the study addresses the following research questions:

What are the publication trends in land degradation and desertification monitoring research from 2021 to 2025?

Which geospatial and remote sensing techniques are most prominently represented in the literature, as reflected by keyword frequency and co-occurrence patterns?

Which spectral indices and environmental variables derived from remote sensing data are most frequently employed in land degradation monitoring research?

What are the dominant land and soil degradation types addressed in the literature, and which geospatial methods are most frequently associated with each type?

To what extent are environmentally vulnerable regions, particularly Central Asia, represented in the global research landscape on land degradation and desertification monitoring?

Novelty in this paper is not the bibliometric approach, which is widely used, but rather in (1) the updated five-year time frame (2021–2025), that can show post-2020 developments, like transition to machine learning and cloud computing, as well as high-resolution satellite monitoring, and (2) the strategic placement of Central Asia into the global context, as a vulnerable dryland area that lacks representation in the literature despite facing severe problems with degradation. This bibliometric approach provides a broader understanding of the current state of research, highlights major scientific trends and collaboration patterns, and identifies potential gaps that should be addressed in future studies.

2. Materials and Methods

The goal of this research was accomplished through the use of bibliometric analysis. Bibliometric analysis is a systematic, quantifiable method that helps to assess and summarize scientific literature in a certain field of research. This method allows identifying research trends, significant researchers, and themes, as well as provides a consistent basis for analyzing vast amounts of scientific articles. In this case, the data for bibliometric analysis were extracted from the Scopus database since this source contains a large amount of high-quality, peer-reviewed scientific articles and utilizes an established system of indexing. In this study, remote sensing and GIS technologies were applied to the problem of desertification and land degradation.

The following inclusion criteria were used to ensure the applicability and reliability of the dataset obtained from the search. Specifically, the Scopus database was searched within the years 2021–2025 in order to consider new trends emerging in the scientific domain. The subject areas of study included only those associated with Earth and Planetary Sciences, Environmental Science, and Agricultural and Biological Sciences. All types of documents except journal articles were excluded from consideration due to their inability to be processed by bibliometric tools, along with non-English language documents.

The following Scopus search query was used:

TITLE-ABS-KEY ("land degradation" OR "desertification") AND TITLE-ABS-KEY ("remote sensing" OR "GIS") AND TITLE-ABS-KEY ("monitoring" OR "assessment") AND PUBYEAR > 2020 AND PUBYEAR < 2026 AND (LIMIT-TO (SUBJAREA, "ENVI") OR LIMIT-TO (SUBJAREA, "EART") OR LIMIT-TO (SUBJAREA, "AGRI")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (LANGUAGE, "English"))

The Scopus database was accessed on 30 March 2026. A total of 2,637 records were initially retrieved. After applying the inclusion criteria and database filters, 2,178 records remained for screening. These records were further evaluated through title, abstract, and keyword screening to assess their relevance to the research topic.

During this stage, 1,523 records were excluded due to irrelevance, lack of focus on remote sensing or GIS applications, or insufficient emphasis on monitoring and assessment approaches. As a result, 655 studies were included in the final dataset for bibliometric analysis. The screening process was conducted manually by the authors. The study selection procedure is summarized in a PRISMA flow diagram (Figure 1).

The analysis was conducted using the Bibliometric package, an open-source tool developed in R for comprehensive science mapping and bibliometric analysis. Bibliometric was selected due to its advanced capabilities in statistical analysis, trend detection, and thematic mapping.

3. Results

3.1 Temporal Analysis of Publication Output

Figure 2 below shows the annual distribution of scientific articles on land degradation and desertification monitoring using remote sensing and GIS from 2021 to 2025, based on the 655 articles included in this study. The results reveal an overall upward trend in scientific output over the period, despite some year-to-year fluctuation. Publication activity was relatively high in 2021, dipped to its lowest point in 2022, and then recovered sharply, reaching a peak in 2025 that was nearly double the 2022 figure. Hence, the results indicate that there is a growing scientific interest in remote sensing and GIS with regard to land degradation and desertification issues.

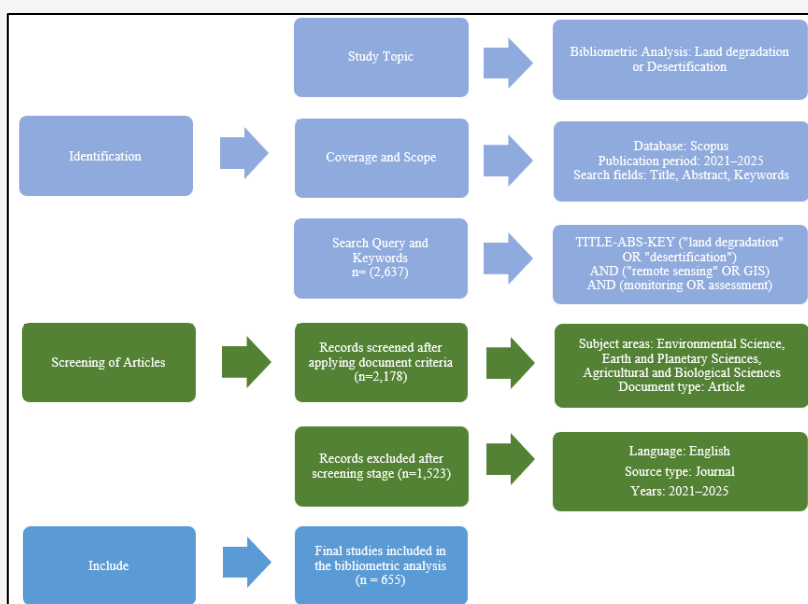


Figure 1: Bibliometric analysis of land degradation study workflow

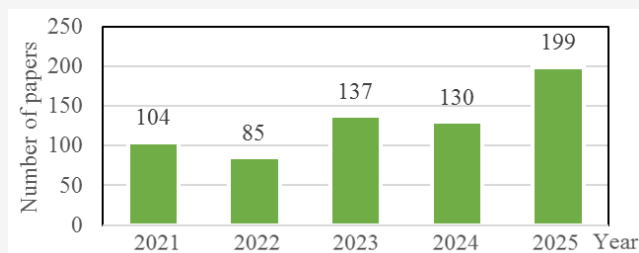


Figure 2: Annual number of publications on land degradation and desertification using remote sensing and GIS (2021–2025)

Table 1: Top journals in GIS-based land degradation monitoring research (Scopus, 2021–2025)

Source	Number of Publications	Total Citation	h-index	g-index	m-index
Remote Sensing	50	927	19	28	3.167
Science of the Total Environment	18	766	14	18	2.333
Ecological Indicators	25	356	13	18	2.167
Environmental Monitoring and Assessment	34	416	13	19	2.167
Land Degradation and Development	35	396	13	19	2.167
Environmental Science and Pollution Research	16	244	12	15	2.000
Sustainability (Switzerland)	21	331	10	18	1.667
Land	31	335	9	17	1.500
Ecological Informatics	7	186	7	7	1.167
Geocarto International	7	111	6	7	1.000

3.2 Key Journals Focused on Desertification Studies

One of the main indicators of bibliometric analysis is to determine which journals contribute the most publications to a particular research area. In this study, the most productive journals reflect the main scientific sources that publish research on our topic. Among these sources of information, the journals that are more active scientifically in terms of the number of articles published and bibliometric impact have been identified, as shown in Table 1. These journals are considered to be the principal channels through which land degradation through remote sensing and GIS can be investigated. Also, the variety of these journals shows that this subject is interdisciplinary, since it combines geospatial technologies with environmental monitoring and land management. Another set of journals, with low numbers of articles published or bibliometric impact, could suggest emerging trends in this field. Table 1 highlights the leading scientific journals contributing to research on monitoring land degradation using remote sensing and GIS technologies. The journals are ranked according to their publication output, total citations, and three widely used bibliometric indicators:

1. The h-index is the number of publications (h) that have each been cited at least h times. In this context, this metric is a combination of publication and citation metrics, which is commonly used to evaluate publication productivity and/or citation impact in a particular set of publications [24].
2. The g-index was developed as an extension of the h-index, providing a greater emphasis on highly cited publications. A journal will be said to have a g-index of g if it has a minimum of g^2 citations for the g most cited publications [25].
3. The m-index is a time-normalized form of the h-index, calculated by dividing the h-index by the number of years since the first publication. This indicator is useful for comparing sources with different publication histories, as it reflects the average annual growth of scientific impact over time [24].

As shown in Table 1, Remote Sensing is the best performing journal, indicating good performance in several bibliometric parameters such as the highest h-index (19) and g-index (28). On the other hand, Science of the Total Environment has the highest

total citations (766) while having published the least number of papers (18). Ecological Indicators, Environmental Monitoring and Assessment, and Land Degradation and Development perform well due to a balance between their publication numbers and citation performances. However, Environmental Science and Pollution Research, Sustainability (Switzerland), and Land make moderate contributions to the field of land degradation research, even though the latter journal publishes more papers than it cites.

3.3 Assessing Author Productivity and Citation Impact in Land Degradation Monitoring

In this part of the analysis, 2,665 authors have been found who have made at least one contribution to the database. Out of these authors, there are only a few who have shown exceptional productivity in publishing their research work. This productivity can be seen in Figure 3, which shows that the highest productivity is shown by WANG Y, who has published 19 papers, followed by ZHANG Y and WANG J, who have published 17 and 16 papers, respectively. Other top authors are ZHANG X (12 papers), CHEN Y, WANG W (11 papers each), and LI X, LIU H, and WANG Z (9 papers each). This figure clearly indicates that the scientific output of the field is limited to a few highly productive authors, while the majority of other authors have contributed comparatively fewer papers. Table 2 also proves that scientific productivity does not necessarily mean a high number of citations. While the most productive scholar is WANG Y, WANG J shows a higher total citation score (412) and a higher h-index score (12). Furthermore, WANG Y and ZHANG Y can be considered the scholars with the greatest scientific

impact due to the high scores of their g-index (17). Other scholars who should be mentioned among those who performed well bibliometrically include ZHANG X, CHEN Y, and ZHANG H. To sum up, it can be stated that the field of land degradation monitoring using the capabilities of remote sensing and GIS technologies is dominated by productive and influential researchers whose works make a great contribution to this domain.

3.4 Affiliation-Based Bibliometric Analysis of Land Degradation Research

The total number of affiliations found in the database is 1,207, demonstrating how many different institutions take part in the study of land degradation monitoring using remote sensing and GIS technologies. As can be seen in Figure 4, institutions located in China dominate the research productivity. For instance, the affiliation that takes the first place is the University of Chinese Academy of Sciences, producing 44 papers, which is a significantly high number compared to other affiliations. Moreover, Xinjiang University and the Northwest Institute of Eco-Environment and Resources come second with the same amount of 21 papers. Third place among Chinese institutions goes to Beijing Normal University, producing 20 papers. At the same time, the Institute of Geographic Sciences and Natural Resources Research, as well as the Xinjiang Institute of Ecology and Geography, provide decent results for the research field too. However, there are other affiliations that do not belong to China that make significant contributions to the research, such as Al-Farabi Kazakh National University, Addis Ababa University, and Northwest A&F University, among others.

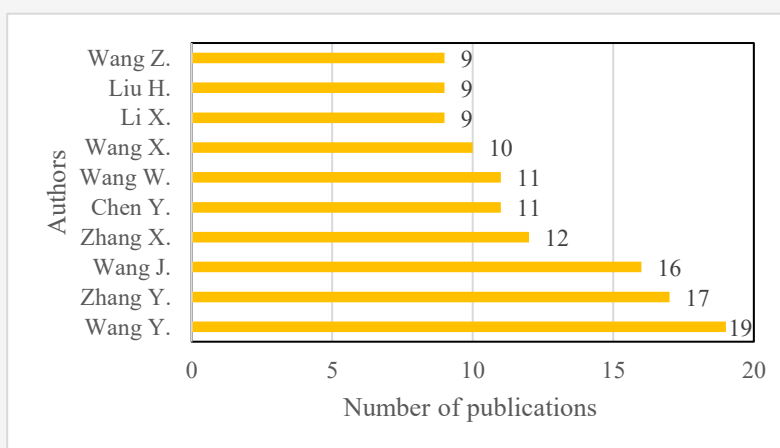
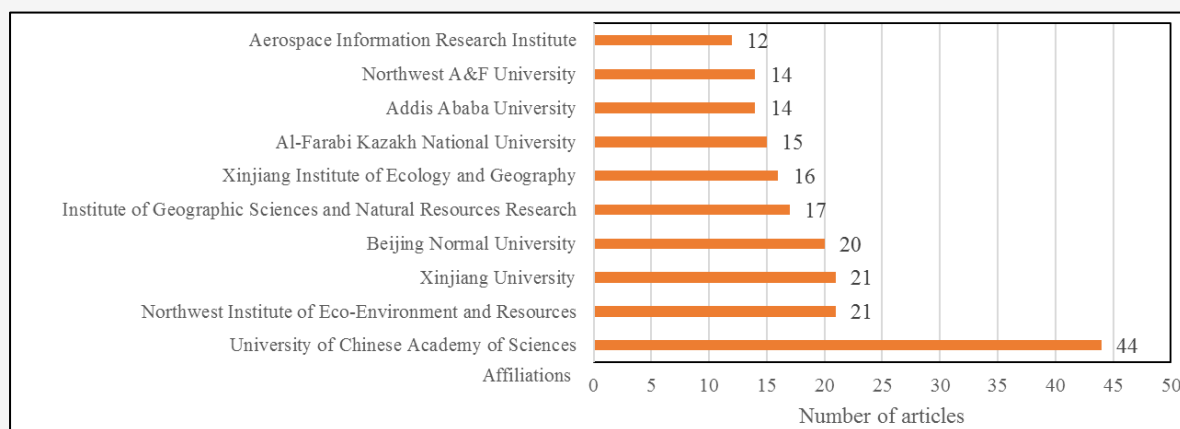


Figure 3: Top contributing authors in land degradation monitoring research (2021-2025)

Table 2: Leading authors based on h, g, and m indices

Authors	Number of Publications	Total Citations	h-index	g-index	m-index
Wang, J.	16	412	12	16	2.000
Wang, Y.	19	312	10	17	1.667
Zhang, X.	12	304	9	12	1.500
Zhang, Y.	17	319	9	17	1.500
Chen, Y.	11	137	7	11	1.167
Liu, H.	9	118	7	9	1.167
Wang, X.	10	174	7	10	1.167
Zhang, H.	9	223	7	9	1.167
Li, X.	9	114	6	9	1.500
Liu, J.	7	113	6	7	1.000

**Figure 4:** Top contributing institutions in land degradation monitoring research

3.5 Geographical Distribution of Research on Land Degradation Monitoring

Based on the geographical distribution of scholarly literature dealing with monitoring land degradation using remote sensing and GIS techniques, it can be concluded that there is an evident bias towards certain countries regarding the output of research. As seen from Figure 5, the leading country in terms of publications is China, which provides the largest number of papers in the field under consideration. There are other countries, such as India, Iran, and the USA, that also make a visible contribution, although the number of their publications is much smaller compared to China's. The leading role played by Asian countries may be determined by the fact that these countries experience serious problems with land degradation, as it has recently become a significant threat because of intense usage, climate change, and poor management

practices. In general, one can note that there is a clear domination of Asian countries in the research output under consideration. The distribution of total citations by country reveals a strong concentration of scientific influence in a limited number of leading nations, as illustrated in Figure 6.

Notably, most of the leading countries are from Asia, highlighting the region's prominent role in this research domain. China is clearly the leading nation, responsible for the highest percentage (44.42%) of total citations, signifying its prominent position and importance in the field of land degradation monitoring research through the application of remote sensing and GIS techniques. Second to China comes India, which makes up 10.90% of the total citations in the area under consideration. Iran and Germany, with 5.30% and 4.34% respectively, also exhibit strong citation performance.

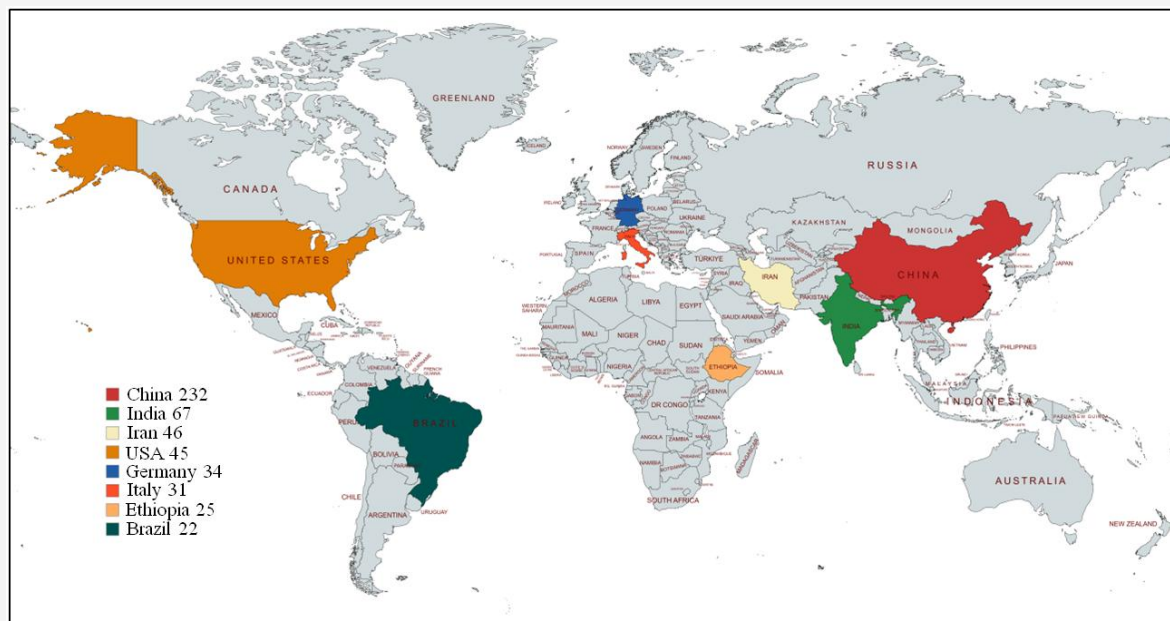


Figure 5: Top contributing countries in land degradation monitoring research

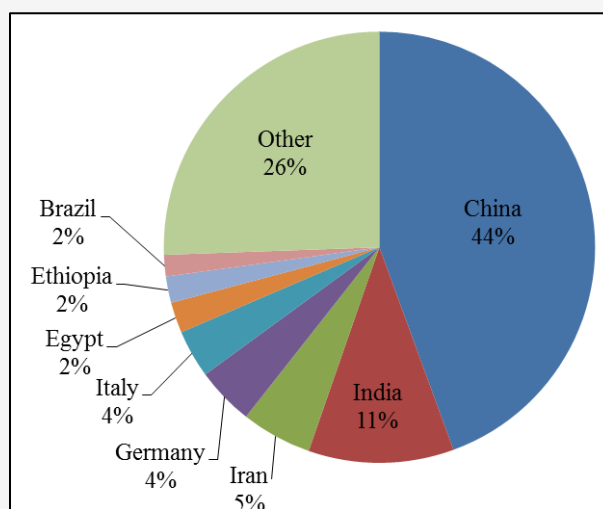


Figure 6: Percentage of most cited countries

Other countries such as Italy, Egypt, Ethiopia, and Brazil make up 3.59%, 2.30%, 1.98%, and 1.61%, respectively, of the total citations. The rest of the countries together comprise 25.56% of the total citations. Citation percentages have an unbalanced distribution, with only a few countries exerting considerable influences in land degradation monitoring research. There are clear disparities in the pattern of corresponding authors in terms of country of origin, which is evident from Figure 7 below. First, there is an abundance of publications

in China, with many of these being SCPs, showing that China has an extensive research capability. However, in addition, there are also many MCPs, highlighting the extent to which China has become involved in international cooperation. India and Iran make substantial contributions, albeit less than those made by China. In both these cases, it can be observed that there are significant proportions of SCPs and MCPs, highlighting both domestic and international collaboration.

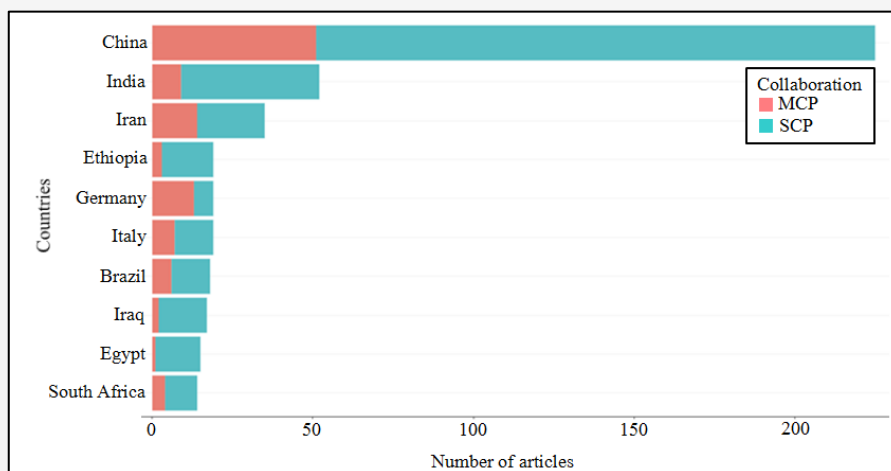


Figure 7: Country distribution of corresponding authors based on SCP and MCP patterns

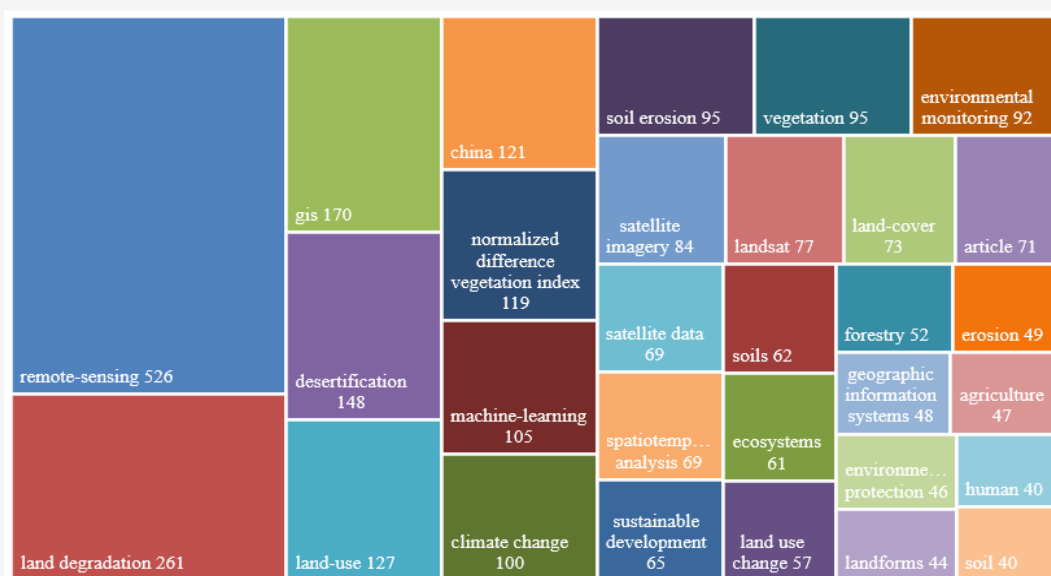


Figure 8: Keyword distribution and research themes

However, in the case of countries like Germany, Italy, and Brazil, the proportion of MCPs is higher relative to their total number of publications. This shows that they are more engaged in international collaboration. A similar case is with developing nations such as Ethiopia, Egypt, and South Africa.

3.6 Keyword Analysis

The distribution of keywords extracted from the analyzed publications is presented in Figure 8. The visualization highlights the most frequently occurring terms and provides insights into dominant research themes in the field of land degradation and desertification monitoring. The keywords that were used the most were remote sensing, which appears in 526 scientific papers (17%); land degradation, which occurs in 261 publications (9%); and GIS,

which was mentioned 170 times as a keyword across the 655 analysed publications (5% of total keyword occurrences). The frequency of occurrence of other keywords includes desertification (148, 5%), land use (127, 4%), and climate change (100, 3%). The high frequency of the above-mentioned keywords confirms the significant importance of geospatial technologies in the investigation of land degradation processes. Moreover, there are several other environmental keywords that are highly frequent, including soil erosion (95, 3%), vegetation (95, 3%), environmental monitoring (92, 3%), and NDVI (119, 4%). The high frequency of soil erosion and vegetation keywords emphasizes the significant interest in the study of vegetation dynamics and processes occurring in soils that are crucial for desertification.

Indeed, the institution, whose node occupies the largest place in the network and connects with numerous other nodes, is that of the University of Chinese Academy of Sciences. One may say that it is crucial to the process of producing scientific output as well as collaborating with other institutes. Such an institution is called a key hub in the research network. It is noteworthy that there are lots of other organizations in China carrying out their research in the discussed field, both located in Beijing and other cities across the country. All in all, the situation testifies to China's role as the leader in this type of research. Also, one can see organizations that work in Central Asia, the Middle East, Europe, and Africa; for instance, some organizations from such countries as Iran, Kazakhstan, South Africa, and Pakistan take part in cooperation. They create very sparse networks, meaning that there is no strong connection like the one between the core participants. Finally, another aspect is regional cooperation in this area. The choice of research partners appears to be connected with the environmental similarity, common interests, and geographic proximity

However, despite some evidence of internationalization within this network, since the network elements are situated on different continents, there is no strong interaction among them.

3.7 Representation of Central Asia in the Global Literature

In order to present a more thorough overview of the historical trajectory of research on this topic in the Central Asian region – a region seriously impacted by land degradation but poorly represented in the recent literature worldwide, the time range for this supplementary research has been expanded to 1991–2025. Otherwise, a narrower time range corresponding to the main dataset (2021–2025) would have resulted in not enough papers for comparative analysis at the regional level. To explore the representation of Central Asia in this area of research, a supplementary search was conducted in which the phrase “Central Asia” was added along with the names of each individual country in the region, namely Kazakhstan, Uzbekistan, Kyrgyzstan, Tajikistan, and Turkmenistan. Thus, in order to identify the long-term evolution of research in this region, the supplementary search period was extended to 1991–2025, covering a more extensive period compared to the main search of 2021–2025. The summary of the numbers obtained is shown in Table 3. Most of the

indexed output originates from Kazakhstan (14 records) and Uzbekistan (8), whereas Kyrgyzstan (3), Turkmenistan (1), and Tajikistan (0) contribute very few records or none. Because land degradation affects all five countries, this distribution is more likely to reflect differences in national research capacity and in access to international publishing than genuine differences in the extent of degradation.

Table 3: Contributing countries in Central Asia identified from the complementary 1991–2025 dataset

Country	Number of Publications
Kazakhstan	14
Uzbekistan	8
Kyrgyzstan	3
Turkmenistan	1
Tajikistan	0

3.8 Methodological and Thematic Content Analysis

3.8.1 Remote sensing data types and platforms

Table 4 shows the types of remote sensing data used in the 655 publications. Clear patterns are recognizable in the analysis. The most frequently cited data source is Digital Elevation Models derived from SRTM (169 papers), indicating the importance of terrain analysis in erosion and desertification studies. The most used satellite platform is the Landsat series data (TM, ETM+, OLI/TIRS), used in 154 papers, appreciated for its long archive that allows a temporal analysis. The use of Sentinel data and high resolution satellite imagery, GaoFen and WorldView, is increasingly important. Google Earth Engine (GEE) appears in 57 papers, reflecting the growing role of cloud computing in large-scale geospatial analysis. MODIS 51 papers, and SAR/Radar data 51 papers, serve complementary roles in temporal and all-weather monitoring, respectively. Drone/UAV data appear in 31 papers, indicating emerging use for high-resolution field-level validation.

3.8.2 Geospatial Methods: digital classification vs. AI/ML-based approaches

The methodological landscape clearly shows a transition from traditional to AI/ML-based methods (Table 5). Nevertheless, the most common technique is NDVI-based spectral analysis (157 papers), which is used as a monitoring indicator and input variable in different types of degradation.

Table 4: Remote Sensing platforms and data types used

RS Platform / Data Type	Number of Publications
Landsat (TM, ETM+, OLI/TIRS)	154
SRTM / DEM	169
Sentinel (1, 2)	71
High-resolution satellite (GF, WorldView)	70
Google Earth Engine (GEE)	57
MODIS	51
SAR / Radar	51
Drone / UAV	31
Hyperspectral	12

Table 5: Geospatial methods applied in land degradation monitoring research

Geospatial Method	Category	Number of Publications
NDVI-based analysis	Spectral/Thematic	157
Machine Learning (general)	AI/ML	102
Random Forest	AI/ML	71
Regression models	Statistical	66
RUSLE / USLE erosion model	Process model	57
Deep Learning / CNN	AI/ML	53
Support Vector Machine (SVM)	AI/ML	33
Change Detection	Temporal	23
Object-based (OBIA)	Traditional	8
Maximum Likelihood Classification	Traditional	6
InSAR	Radar	2

General machine learning methods are reported in 102 papers, Random Forest in 71 papers and Deep Learning/CNN in 53 papers among machine learning and AI methods, contributing to an approximate 35% presence of AI/ML in the corpus. Statistical regression models are applied in 66 papers, and physics-based erosion models (RUSLE/USLE) in 57 papers. Conventional digital classification techniques – Maximum Likelihood and Object-Based Image Analysis (OBIA) – are present in just 14 papers combined, confirming the fact that the use of AI/ML-based approaches have, for the most part, replaced traditional classification methods in recent land degradation monitoring research. A total of 290 papers (44.3% of the corpus) incorporate temporal or multi-temporal remote sensing data, as evidenced by keywords and abstract mentions of terms such as 'time series', 'multi-temporal', 'inter-annual', 'seasonal', 'trend analysis', and 'change detection'. This proportion underscores the centrality of temporal monitoring in land degradation research, particularly for detecting long-term vegetation decline, desertification progression, and LULC transitions over time.

3.8.3 Spectral Indices and Environmental Variables Beyond NDVI

The most frequent spectral index in 164 papers is NDVI. However, a range of complementary indices

is used in the literature for specific soil and vegetation properties (Table 6). Land Surface Temperature (LST) and Salinity Index (SI) appear each in 41 papers, indicating the importance of thermal and chemical soil properties in degradation monitoring. The NDVI is not reliable in areas of sparse vegetation where the soil background interferes with the NDVI, SAVI 34, and MSAVI 17 are used. The Bare Soil Index 15 papers is a specific index of exposed soil related to desertification and erosion. NDWI (13 papers) and EVI (12 papers) capture water content and enhanced vegetation response, respectively. SWIR-based indices (5 papers) are used in soil moisture and salinity applications. This diversity of indices indicates that the field has moved beyond simple greenness measures toward multi-variable characterisation of land condition.

3.8.4 Dominant land and soil degradation types

The literature addresses a range of land and soil degradation types (Table 7). Desertification is the most frequently addressed type 282 papers, consistent with the query scope. Soil erosion by wind and water is the second most common 153 papers, followed by land use/cover change 128 papers, and vegetation degradation 123 papers. Salinisation and alkalinisation, a critical form of chemical soil degradation particularly prevalent in

irrigated dryland areas, is addressed in 85 papers. Drought stress is referenced in 66 papers. Terrain deformation encompassing gully formation, mass movement, and slope instability appears in 58 papers, primarily through DEM and SAR-based methods. Soil organic matter loss and soil quality decline are covered in 50 and 42 papers respectively, increasingly using regression and machine learning approaches on multispectral data. Sandy and aeolian degradation appears in 37 papers.

3.8.5 Geospatial methods associated with each degradation type

Table 8 presents a cross tabulation between degradation types and the geospatial methods most frequently associated with degradation types based on keyword and abstract co-occurrence analysis. Soil erosion research is dominated by RUSLE/USLE process models (56 papers) coupled

with Landsat imagery and NDVI for vegetation cover assessment. Erosion: 17 papers, again showing increased adoption but not yet dominance of ML/AI methods. Desertification studies present the widest methodological variety: ML/AI (62 papers), NDVI-based analysis (67), and GEE-based processing (28) are all well represented, consistent with the complexity and scale of desertification processes. The heaviest basis of studies focused on salinisation and alkalinisation is Salinity Index and ML/AI classification (30 papers), followed by regression models (16 papers). LULC change studies use the widest range of methods, including ML/AI (34), change detection algorithms (13), and RUSLE (20) where land use relates to erosion risk. Terrain deformation studies are the most methodologically specialised, relying almost exclusively on DEM analysis, with very limited ML/AI uptake (4 papers).

Table 6: Spectral indices and environmental variables identified

Spectral Index / Variable	Primary Application	Number of Publications
NDVI	Vegetation condition	164
LST	Thermal degradation, drought	41
Salinity Index (SI)	Soil salinisation	41
SAVI	Vegetation in sparse areas	34
MSAVI	Minimised soil noise	17
BSI	Erosion, desertification	15
NDWI	Water body / moisture	13
EVI	Dense vegetation	12
NDSI	Soil / snow	6
SWIR-based indices	Soil moisture, salinity	5
LAI	Vegetation structure	5

Table 7: Dominant land and soil degradation types addressed

Soil / Land Degradation Type	Dominant Method	Number of Publications
Desertification	ML/AI + NDVI + GEE	282
Soil erosion (wind & water)	RUSLE/USLE + Landsat	153
Land use/cover change	ML/AI + Change Detection	128
Vegetation degradation	NDVI + Landsat/MODIS	123
Salinisation / Alkalinisation	Salinity Index + ML/AI	85
Drought	NDVI + MODIS + LST	66
Terrain deformation	DEM + SAR	58
Soil compaction / quality	Regression + ML	50
Soil organic matter loss	Regression + Hyperspectral	42
Sandy / aeolian degradation	High-res satellite + DEM	37

Table 8: Geospatial methods by degradation type

Degradation Type	ML/AI	RUSLE/USLE	NDVI	Regression	Change Detection	SAR	GEE	Total
Soil erosion	17	56	31	9	3	11	12	153
Desertification	62	5	67	29	11	22	28	282
Vegetation degradation.	4	2	13	5	1	0	3	123
Salinisation	30	1	22	16	2	6	1	85
LULC change	34	20	33	9	13	7	16	128
Drought	13	1	21	4	5	3	6	66
Terrain deformation	4	4	2	1	0	0	0	58
Soil organic matter	8	5	12	2	0	1	5	42

4. Discussion

The bibliometric findings of this study can be read on three levels: the uneven distribution of research output across countries and institutions, the mismatch between where land degradation is most severe and where it is most studied, and the methodological challenges that shape the reliability of remote-sensing-based monitoring.

4.1 Concentration of Research Output and Its Drivers

The results describe a markedly uneven research landscape. A small number of countries, led by China, account for a disproportionate share of both publications and citations, and the institutional collaboration network shows a core-periphery structure in which a few well-resourced institutions occupy central positions while most others remain peripheral. This concentration is unlikely to mirror the geography of land degradation itself; instead, it follows the familiar determinants of scientific productivity. Countries with sustained national investment in Earth-observation programmes, larger research workforces, and better access to satellite data and high-performance computing can publish more and accumulate more citations. Part of the imbalance is also an artefact of how bibliometric databases are constructed: Scopus indexes predominantly English-language journals, so research published in national languages or in non-indexed outlets is systematically undercounted, which inflates the apparent dominance of some countries and obscures the contributions of others [26]. Similar patterns of concentration recur in bibliometric studies of related environmental fields, which suggests that the effect is structural rather than specific to this topic [27]. The practical implication is that global research priorities may be shaped by where scientific capacity already exists rather than by where degradation is most acute, which can slow the development of locally grounded monitoring approaches.

4.2 The Mismatch between Degradation Severity and Research Attention

One of the most important findings from this study is the disparity between the areas experiencing the highest degree of land degradation and the areas getting the most scientific attention. The country-level results, combined with the Central Asia assessment in the Results section, show that some of the areas experiencing the highest levels of degradation pressure are still underrepresented in international research [28] [29] and [30]. Central Asia illustrates this gap clearly. Although the region is highly vulnerable to salinization, wind and water

erosion, and desertification, and although the desiccation of the Aral Sea is one of the most severe human-induced environmental disasters of recent decades [31] and [32], the volume of indexed research remains modest.

The imbalance is repeated at the national scale: as shown in the Results section, Kazakhstan and Uzbekistan produce most of the regional output, whereas Kyrgyzstan, Tajikistan, and Turkmenistan are barely represented. Since degradation affects all five countries, this internal gap is consistent with differences in research capacity, funding, and access to international publishing, although a direct causal test lies beyond the scope of this bibliometric analysis. It is unlikely to reflect any real difference in the severity of the problem [28] and [33]. When combined, such patterns provide a compelling argument for strategic capacity development in these vulnerable areas through investments in monitoring facilities, training, and publication support, thereby ensuring that the scientific literature more accurately portrays the reality of land degradation and its distribution to help guide policy decisions. This is clearly shown in Figure 11 below, which shows that the areas that suffer the most from both arid conditions and land degradation include North Africa, the Middle East, the Sahel, some parts of sub-Saharan Africa, and Central Asia.

4.3 Methodological Challenges in Remote-Sensing-Based Monitoring

Beyond these structural patterns, the literature highlights recurring methodological challenges that shape the reliability of monitoring. Remote sensing and GIS have greatly expanded the capacity to track land degradation across large spatial and temporal scales, offering synoptic, repeatable, and multi-temporal observation that is especially valuable where field-based monitoring is difficult or costly [18] and [34]. However, satellite-based assessments do not always align with field measurements because land degradation is a multifaceted process involving physical, chemical, and biological dimensions that cannot all be captured from space; remote sensing, therefore, complements rather than replaces field observations [35] and [36]. Validation is the key difficulty. Mapped degradation patterns need to be checked against ground-truth, field, or survey data, yet the validation of remote-sensing products in this field has often been limited or insufficient [37] and [38]. A further issue is that different indices, thresholds, and modelling choices can yield different estimates of severity: proxy variables such as NDVI and net primary productivity, which are widely used in large-scale studies, must first be corrected for the confounding

effects of rainfall, climate, and land use before they can be interpreted as degradation signals [36] and [39]. These challenges indicate that future monitoring should integrate remote sensing and GIS with locally relevant field-based assessment and ground-truth data, so that degradation estimates become more robust, consistent, and useful for decision-making [20].

4.4 Future Research Directions

Future research on land degradation monitoring by means of remote sensing and GIS technology will see considerable progress due to the incorporation of cloud computing, artificial intelligence, and high-resolution imagery. Such trends open up new possibilities for enhancing the effectiveness of land degradation assessments, especially in data-poor areas like Central Asia [40] and [41]. One way that could be considered as a possible solution is the increasing use of geospatial cloud computing solutions such as Google Earth Engine (GEE). These offer the advantage of being able to perform computations on big volumes of satellite data and enable people to get access to data about the Earth from archives. This makes it easy to study how land has degraded over time through observation [42].

In recent times, several studies have shown that cloud computing technology greatly enhances the effectiveness and reliability of environmental monitoring through quick data analysis and the integration of multiple datasets such as climatic factors, land use practices, and vegetation indices [43] and [44]. Therefore, it can be anticipated that the use of such systems will be instrumental in future studies on land degradation, especially in those areas where access to data and computing facilities is scarce. Land degradation monitoring is one area where ML and DL technologies have gained popularity as an emerging trend. These technologies have exhibited great promise in increasing classification accuracy, analyzing intricate spatial patterns, and predicting degradation trends [45]. Conventional machine learning approaches like Random Forest and Support Vector Machine are commonly employed in land cover classification and degradation mapping on account of their resilience and efficiency [45]. Convolutional Neural Networks (CNNs) are relatively new additions to the realm of machine learning and have exhibited an upper hand in recognizing fine-scale details from images [46].

However, these techniques depend on having extensive training sets and ground truth information. The problem is that, in many areas of the world, including Central Asia, this information is not available. Thus, future studies need to be aimed at

expanding the availability of training data and at increasing model generalization across regions [47]. Hyperspectral remote sensing technology is another emerging area for the development of monitoring programs of land degradation. Unlike conventional multispectral imaging systems, which acquire data from a few spectral bands, hyperspectral imaging can provide data from hundreds of spectral bands [48]. The highly sensitive spectral characteristics also make it possible to identify factors contributing to land degradation that cannot be seen through other traditional methods, such as NDVI, for example, soil salinity levels, organic matter composition, or vegetation stress. It can be expected that, as more hyperspectral missions are launched on satellites, land degradation assessments will greatly improve their accuracy [49]. However, problems associated with high dimensions, computational difficulty, and the requirement of complex analytical techniques are still prevalent. The future scope of research is to adopt dimensionality reduction techniques that involve the use of hyperspectral data and its fusion with machine learning techniques, along with field data for better verification [50].

4.5 Limitations of the Study

Several limitations should be considered when interpreting these results. First, the analysis relies solely on the Scopus database and includes only English-language journal articles; relevant work indexed elsewhere (for example, in Web of Science or in regional and non-English journals) is not captured, which may further underestimate output from under-represented regions such as Central Asia. Second, author-level indicators are based on Scopus author disambiguation using surname and initials, which may merge or separate records belonging to different individuals; therefore, author rankings should be interpreted with caution. Third, the results are sensitive to the specific search query, subject-area filters, and manual relevance screening applied, meaning that alternative query designs may yield different datasets. Fourth, the prominence of particular countries and institutions reflects database coverage, publication volume, and citation practices, including self-citations, rather than scientific quality alone.

Finally, the supplementary Central Asia analysis is based on a separate dataset with a different search query and time span (1991–2025) and a relatively small number of records; therefore, Table 3 and related findings should be interpreted as indicative rather than conclusive. The Scopus database was accessed on 30 March 2026, and while publications up to 2025 are treated as complete at the time of

extraction, minor discrepancies may still exist due to indexing delays in the database.

5. Conclusions

This study provides a comprehensive bibliometric review of land degradation and desertification monitoring using remote sensing and GIS. Based on the Scopus database, a total of 655 peer-reviewed journal articles published between 2021 and 2025 were analyzed to identify scientific trends, leading journals, influential authors, major institutions, contributing countries, and potential future research directions. It was found that the scientific activity level increased during the analyzed years. Moreover, remote sensing and GIS methods turned out to be the key instruments that help monitor changes of land degradation. The methodology of remote sensing for studying land degradation has also continued to advance, with recent research increasingly employing techniques such as machine learning, cloud computing, and satellite observations. In addition, the results reveal the disparity in research output and its citation impact between countries and institutions. While certain countries like China show a dominance in terms of publications and scientific influence, areas that experience heavy impacts of land degradation – for instance, Central Asia, parts of Africa, and the Middle East – receive little attention in the scientific literature. Clearly, there is a need for greater capacity building, better access to information, and increased collaboration from the side of the scientific community to solve the problem.

While there have been many advances in the assessment of land degradation processes, there are still certain gaps to be addressed. They include limitations in the use of field data and the validation of remote sensing-based techniques, as well as methodological problems. In summary, this work makes a valuable contribution to the existing body of knowledge regarding land degradation and desertification monitoring. Further studies should concentrate on enhancing the validity of the assessment through the use of more accurate techniques and field data.

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