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On the emergence of geospatial cloud-based platforms for disaster risk management: A global scientometric review of google earth engine applications

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ABSTRACT

With the global upsurge in climatic extremes, disasters are causing significant damages. While disaster risk management (DRM) is a serious global challenge, governments, stakeholders, and practitioners among many other actors seek advanced solutions to reduce disaster-related costs. Recently, Google Earth Engine (GEE), a cloud platform used for planetary-scale geospatial analysis using big-data, has gained popularity due to its applications in various fields. While the availability of free satellite data has facilitated long-term spatial-temporal trends and patterns identification, cloud computing emerged as a reputable tool in geo-big data analyses. Yet nearly after ~15 years of its launch, the impact of such cloud-computing platform on DRM (risk assessment, monitoring, and planning) has not been carefully explored. Hence, a systematic review regarding the current state and trends in GEE applications to DRM is needed, which could provide the community with the bigger picture of the subject matter. Therefore, this study aims to investigate the advancement in DRM with GEE being the primary platform used. For this, 547 peer-reviewed studies published in 208 different journals during 2010–2022 were assessed. The current spectrum of GEE applications is dominated by floods, drought, and wildfires. For data type, most of the studies used optical data (Landsat and Sentinel-2). In terms of geographical distribution, China, USA, and India dominate with highest articles published. Within this research domain, three emerging research themes (floods, forest fire, and classification) are observed. Our findings signify the emergence of GEE applications in DRM, which will continue making substantive progress on DRM-related multi-scale challenges.

1. Introduction

1.1. Disaster risk management (DRM) background

A disaster is a sudden catastrophic event that jeopardizes the self-surviving ability of a particular community or society. Disaster and hazard are interrelated terms and are often confused. A hazard is any damaging phenomenon; in contrast, it is considered a disaster when it involves human agency [1]. Disasters fall into two broad categories: natural (floods, earthquakes) or man-made disasters (nuclear explosions, pollution). Although their origin differs, their gap is diminishing with human interventions. With the rapid surge in global environmental issues, including urbanization and climate change, there is a noticeable increase in the frequency and dura-

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tion of hazards [2]. Anthropogenic activities are accelerating natural hazards at an alarming rate, pushing the planet towards existential limits. Annual disaster events frequency increased by ~40 % in 2021 compared to 2015 (United Nations Office for Disaster Risk Reduction (UNDRR) [3]. Increased frequency of disasters will eventually result in more significant economic loss, thus compromising long-term sustainability at various scales (i.e., global, national, and sub-national). According to the UNDRR report, over the past three decades, the financial losses resulting from disasters have increased by an average of ~145 %, from $70 billion in 1990 to more than $170 billion in 2010 [4]. In 2021, the Emergency Event Database (EM-DAT) recorded over 432 disaster events globally, which caused ~10,492 deaths, affected ~102 million people, and resulted in ~$252 billion in economic loss (~260 % increase in financial loss from 1990) [5]. While disasters are inevitable, risk management is imperative to ensure effective and coordinated response to disaster, thus ensuring long-term sustainability.

According to the Global Risk Report [6], the risk category "*natural disasters and extreme weather events*" is ranked second and third place globally for the next 2 and 10 years, respectively. Over the years, disasters have caused substantial damage to property, natural resources, human life, and health along with disrupting socio-economic activities. Among all types of natural and man-made disasters, floods, storms, earthquakes, wildfires, drought, and landslides have dominated in the last decade. In 2021, 206 flood events were recorded, resulting in ~4393 deaths, the highest among other disasters. Besides, flood events in 2021 also resulted in ~USD 746 billion in economic loss, affecting ~30 million people globally [7]. Other than floods, storm events contributed to the highest economic loss of ~USD 1376 billion, while drought events affected the highest of ~55 million people globally in 2021. Nearly in all disasters, over the years, the human life casualties have severely reduced, specifically in developed regions (such as Norway), which showed greater resilience towards such events, whereas the least resilient developing nations (e.g., Yemen) still suffer [5,8]. While the death rate is reduced, the economic loss resulting from the increased frequency and duration of disasters is significant and is increasing at an alarming rate [7]. This situation emphasizes the need for frameworks to minimize the disaster-triggering factors and monitor disaster events, which will eventually save lives and future proof sustainable development.

While DRM utilizes various frameworks and methods for minimizing disaster triggering factors and monitoring disaster events, each has its strengths and weaknesses. For instance, hazard mapping and risk assessment offer valuable insights for planning and preparedness but are limited by data uncertainties and the difficulty of incorporating dynamic factors like climate change [9]. Early warning systems save lives through timely information, but face challenges of reaching vulnerable populations and false alarms [10]. Community-based approaches empower local communities and promote resilience yet require external support and coordination [11]. Simulation and modeling inform decision-making but rely on high-quality data and face uncertainties [12]. Public awareness and education campaigns empower individuals, but struggle with reaching diverse populations and maintaining long-term engagement [13]. By recognizing these strengths and weaknesses, practitioners can adopt an integrated approach to enhance DRM and build more resilient communities. This involves leveraging the strengths of each method while addressing their limitations, leading to a more comprehensive and effective approach to DRM.

1.2. Remote sensing and earth observation data

Remote Sensing (RS), which is the science of monitoring the physical characteristics of an area from a distance, usually from aircraft or satellites, has been excessively used for disaster risk assessment, profiling, and planning regardless of the scale of the study [13–16]. Risk management is a sequence of processes including planning, organizing, coordinating, and implementing measures to respond to disasters. While DRM has a broad scope, there are four different phases including prevention, preparedness, response, and recovery (Fig. 1) [17]. The advancement in geo-information-based tools and techniques, along with multi-temporal earth observation satellite (EOS) data, allows effective risk assessment with reliable outcomes [16]. With the availability of multi-source satellite datasets over the past decades, many new possibilities are emerging. At the same time, some hurdles and challenges also unfold such as, the high storage, computational power, and processing needs. For instance, there is a hot debate on storing, processing, and interpreting satellite data explicitly used for risk assessment [17–21]. Collectively, data from different sources that are difficult to manipulate (i.e., store, manage, and process) via utilizing traditional approaches and tools is called big data [22], and present technological paradigm that enables a researcher to analyze large amounts of data efficiently through specific practices. With the advancement in

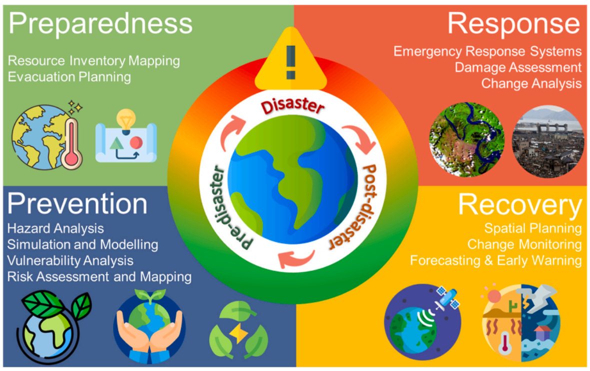


Fig. 1. Disaster management phases and the role of remote sensing.

geospatial data acquisition and storage, remotely sensed data have exceeded the exabyte scale, with up to petabytes generated yearly [21].

To address processing-related challenges in geo-big data analysis, platforms are grouped into cluster-based high-performing computing (HPC) systems and cloud computing platforms. In cluster systems, various computers are linked through interconnected servers, which allows processing load to be divided to every available node (computer), therefore analyzing efficiently [23]. This technique has proved beneficial in different RS domains, especially in analyzing data from local data sources (i.e., drone images and local survey data). However, the main drawbacks of HPC clusters include the economic cost of purchasing and maintaining hundreds of nodes, high time and cost required for data importing from the servers, and upfront cost on technicians' team for handling such clusters [24]. On contrary, cloud computing platforms involve analyzing data internally without relying on local hardware. This virtualization makes cloud computing more robust and efficient since all the data mining, cleaning, processing, and interpretation is done on internet servers [25]. Similar to HEC clusters, cloud computing platforms also use multiple node-serves, which provide efficient data processing by dividing the workload. However, cloud computing dominates, as it requires minimal initial cost or subscription to run a specific process and does not require maintenance costs [14].

In the last decade, applications of cloud computing in the RS field have increased, covering many sectors, including disaster risk assessment. Currently, many companies are providing cloud services for geo-analytics at a much more affordable rate, with nearly free access to petabytes of RS data. For instance, Amazon web services (AWS) is the earliest known cloud service, adopted widely after its launch in 2006. AWS works on the Laas model and provides many services in the domain of geo-analytics by applying core technologies such as machine learning, artificial intelligence, data lakes and analytics and internet of things [26]. AWS provides planetary-scale applications with the name "*Earth on AWS*", which are explicitly designed to help monitor long-term sustainability. Furthermore, different geospatial datasets, including Sentinel-2, United States Geological Survey (USGS) Landsat-1 to 9 missions, National Oceanic and Atmospheric Administration (NOAA) Geostationary Operational Environmental Satellites (GOES) (GOES mission16, 17, and 18), European Space Agency (ESA) provided land-use land-cover (LULC) and so on [27]. After AWS, Microsoft developed the cloud platform "Azure" in 2010, which handles data storage and analytics through Microsoft-managed data centers. Compared to AWS, Microsoft has much more machine learning services, complemented by the addition of open-source datasets, including Landsat, Sentinel, NOAA, Moderate Resolution Imaging Spectroradiometer (MODIS), and others [28]. International Business Machines (IBM) also started providing cloud-related services after 2011. They targeted small to large organizations by providing them with public, private or hybrid storage and networking facilities based on all three cloud models (Laas, Paas, Saas) [29].

1.3. Google earth engine platform

Google Earth Engine (GEE), a web-based geospatial cloud application hosted by GCP, revolutionized the way we interact with RS data. Since the launch of GEE in 2010, it has remained free for academic and research use, along with providing specific quotas for commercial utilization. GEE is recognized primarily due to its fast and interactive algorithm development and implementation, instant access to multi-petabyte EOS data catalog, and its ability to host web-based applications for interactive visualization and communication of the findings [25].

GEE provides a simple web-based interface that can be utilized using JavaScript programming language. This web-based explorer provides data catalog, visualizations, and map results at fingertips. While GEE web-based interface (available at: code.earthengine.google.com) is widely used, other interfaces emerged recently, categorized based on end platforms. GeeMap, a python-based, a recently developed module, is well-recognized for python-based GEE applications [30]. Furthermore, GEE integration with well-known Geographic Information System (GIS) software, including Quantum GIS (QGIS) and ArcGIS Pro (provided by the Environmental Sciences Research Institute—ESRI) is also now available. This wide adoption allows GEE to be used in multiple domains, including agriculture, hydrology, atmosphere and climate, pedosphere, image processing, and disasters.

Recently, GEE surfaced as a prominent platform for disaster risk assessment and profiling [31,32]. Many new possibilities have emerged with its Near Real Time (NRT) data acquisition, storage, and processing capabilities. The main issue with conventional disaster risk assessment is the innate unpredictability of different types of hazards, which altogether possess challenges for a single solution exploration. However, in GEE, the native availability of different RS platforms and sensors with their varying spatial, spectral, and temporal coverage provides crucial information, progressive assessment opportunities, and objective data used by scientists and policymakers to understand the spatial phenomenon and ultimately for effective on-time decision-making [33–36]. Many recent studies have highlighted potential trends and applications of GEE [14,31,32]. However, nearly all lack addressing the detailed emerging trends of GEE application in DRM. Moreover, there is no comprehensive study exploring the specific trends in several aspects of ongoing scientific works, such as author collaborations, citations, institutional engagements, geographical distributions, key publishing journals, and significant research themes concerning GEE and DRM. This situation suggests an urgent need for a comprehensive review to explore GEE applications in DRM. Such a review will help uncover the current state and trends in GEE applications to DRM, which could provide the community with the *bigger picture* of the subject matter. Thus, this review study aims to provide a comprehensive survey of emerging research in DRM, utilizing GEE as a primary platform for data storage, acquisition, analysis, and visualization both local to regional scales. To do so, a systematic and scientometric analysis is carried out using the data from global archives of scientific literature. As a result, the published literature on the subject matter during 2010–2022 is identified, evaluated, and categorized for insights related to harnessing the power of GEE for effective DRR. This study could potentially act as a roadmap as well as a reference for people seeking literature and state of the applications of GEE in DRM to take additional research in this field.

2. Materials and methods

Web of Science (WOS) and Scopus databases were used individually for relevant literature search. The search query was designed in a specialized way to cover all the studies using the keyword "Google Earth Engine" with several hazards (i.e., Floods, Forest Fires, Landslides, Tropical Cyclones, Earthquake, and drought) and risk assessment, hazard, and disaster. For reference, the exact search query is given as:

("Google Earth Engine" OR "Earth Engine") AND ("Flood*" OR "Forest Fire*" OR "Landslide*" OR "Tropical Cyclones*" OR "Earthquake*" OR "Drought*") OR "Google Earth Engine" AND ("Risk Analysis" OR "Risk Assessment" OR "Hazard*" OR "Disaster*")

The query was applied to the aforementioned databases on 13th October 2022, and as a result, we initially filtered 881 publications between 2010 and 2022. To follow along, we adopted the methodology known as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which defines the search and filtering criteria for scientometric analyses [37]. The schematic of PRISMA workflow is shown in Fig. 2. Initially, 503 articles from Scopus and 378 from WOS were taken. These articles were screened, and only articles in the English language were taken. As a result, 4 articles from WOS and 18 from Scopus were removed due to language screening. The resulting two databases were then analyzed using computer-aided bibliometric software, specialized in bibliometric analysis.

Bibliometric analysis is a review methodology involving the use of computer-assisted tools and techniques based on a given topic that analyzes different trends and relationships. For this study, we utilized two bibliometric software including Bibliometrix and VOSviewer. The Bibliometrix software, is natively developed in R language and contains a complete set of tools for science mapping workflow (available at: www.bibliometrix.org). For this software, we used R Studio build 576, with R language version 4.2.1. Recently, the platform developed a web-based application called Biblioshiny, designed explicitly for performing bibliometric analyses with a more intuitive Graphical User Interface (GUI) [38]. On the other hand, VOSviewer is a complete computerized software provided by Leiden University and is well-known for visualizing bibliometric networks [39] (available at: www.vosviewer.com). As both Bibliometrix (including RStudio, R-language) and VOSviewer, of these tools are freely available for educational purposes, their selection was the most optimal choice to conduct several analyses reported in this study.

Filtered papers from both databases (i.e., WOS and Scopus) were combined using RStudio and Bibliometrix-library packages. First, these databases were exported in Comma Separated Values (.csv) format from WOS and Scopus and were converted into R-DataFrame using Bibliometrix module named "*convert2df*". Then, both R-DataFrames (WOS and Scopus) were merged into a single R-DataFrame using Bibliometrix "*mergeDbSources*" module. During this process, the program indicated 312 duplicate papers, common in both databases. We merged these duplicates and resultantly, a total of 547 papers were taken. Lastly, the R-XLSX package was used to export merged R-DataFrame into. XLSX format, which is natively supported by Biblioshiny web-based app.

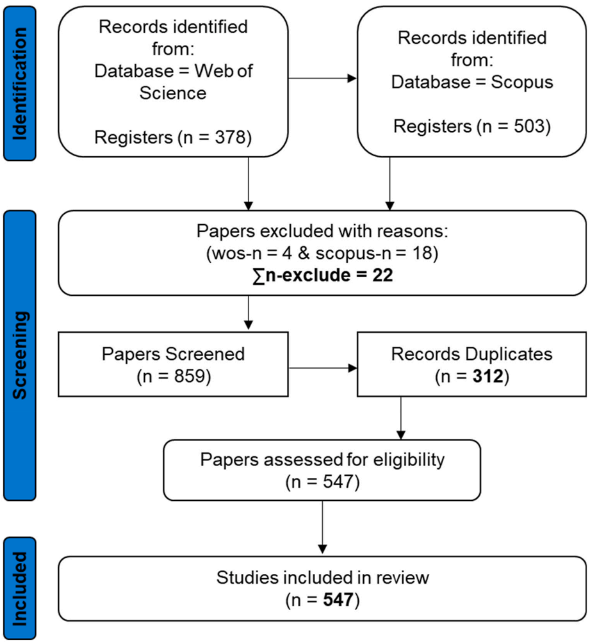


Fig. 2. Prisma flowchart.

3. Results and discussions

3.1. Overview of the materials selected for the review

A total of 547 studies are collectively taken for bibliometric analysis, published by 1961 authors. After the official launch of GEE (2010), the first study on disaster risk assessment utilizing GEE came in 2014. Since then, this domain has observed an exponential annual growth of ~75 % (Fig. 3a). The upcoming results will focus on the nature of articles, authors and institutions, source dynamics including journals and countries, knowledge hotspots, research themes, thematic areas, and research keywords evolution in this field of research.

In general, a summary of included articles is presented in Fig. 3a, and it is evident that 547 total articles appeared in 208 sources (i.e., journals). These studies contain 1707 author-defined keywords, with an average of ~5 authors contributing to each paper. During article filtering, we included every possible peer-reviewed article, which was later categorized as full-text articles, early access accepted articles, conference reviews, full-text review papers, and data papers. Among these types, full-text articles account for 75 % of the total papers, whereas early access, conference review, and data paper account for 2 %, 2 %, and 1 %, respectively (Fig. 3b). It is observed that among 547 studies, 75 % consist of journal articles, regarded as commonly published material in disaster risk assessment with GEE studies. Followed by articles, significantly fewer studies comprised early access and conference papers (<2 %), thus highlighting the ratio difference (with journal articles) and common preferences of authors.

3.2. Categorization of disasters

Several disaster categories are identified based on the review of journal articles, and studies are filtered based on each disaster keyword. The keywords identified are further generalized into similar groups and are finally categorized into 9 groups representing each discipline. The graphical representation of major disaster studies involving GEE is shown in Fig. 4. It is observed that studies addressing flood issues are the highest as compared to other natural hazards, with an accumulative 191 published papers, followed by drought (121) and wildfire (69). In the floods category, most of the studies focus on flood inundation mapping, risk assessment, hydrological modeling, and flood forecasting. Further details of each research keyword are provided in section *3.4*. Thirty-five studies focused on Landslide hazard-related issues (including risk susceptibility and damage assessment), whereas the snowstorm category (avalanches, blizzards, glaze, silver storm) was explored in 28 studies. Studies addressing different types of earthquakes (tectonic, volcanic, collapse, and explosion) are 13, followed by the tropical cyclone discipline having 18 studies. Lastly, comparatively least among other disaster types, 8 volcanic eruption-related studies are identified. Excluding these significant disaster studies, 64 studies belong to distinct groups such as risk, hazard, vulnerability, susceptibility, and others.

3.3. Emerging trends in data usage for DRM

Fig. 5 shows a noticeable increase in disaster management studies, from only 2 in 2014 to 172 in 2022. A significant increase in the number of papers is observed since 2019 (9 years after the start of GEE as a cloud service). Furthermore, the increasing trend continued to grow yearly. For different data types utilized for the analyses, optical data are the prominent data type used initially, followed by the Synthetic Aperture Radar (SAR) after 2016. The utilization of optical data (from Landsat, Sentinel-2, and MODIS) in disaster management studies using GEE grew after 2019. Similarly, after 2019, a rapid increase is observed in studies using Sentinel-1 SAR data as their primary source for disaster risk assessment through GEE. The combination of optical and radar data (multi-source data including Landsat, Sentinel-1, Sentinel-2, and MODIS) is still in the initial progressing stage.

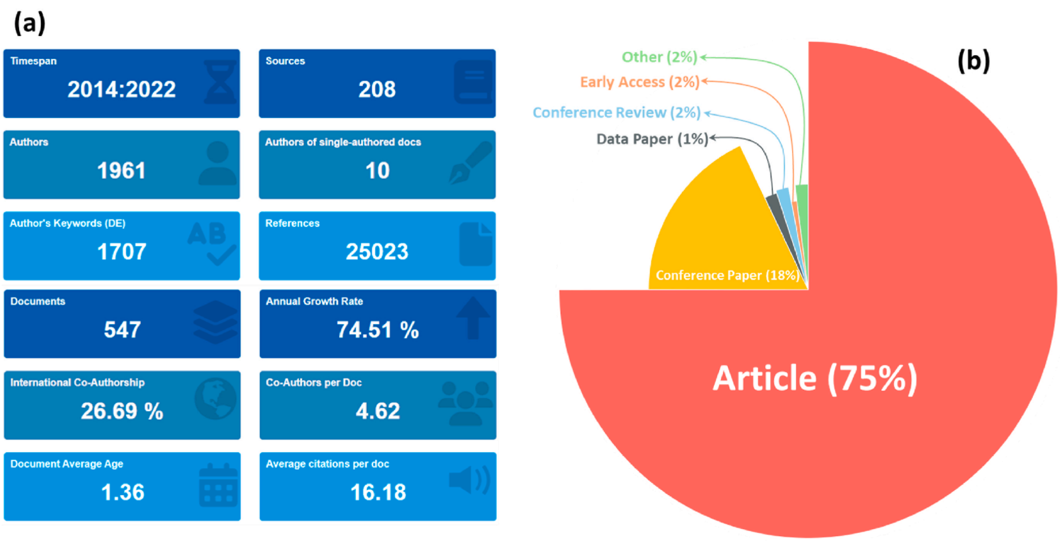


Fig. 3. (a) Brief summary of the included studies and (b) Article categories based on their types.

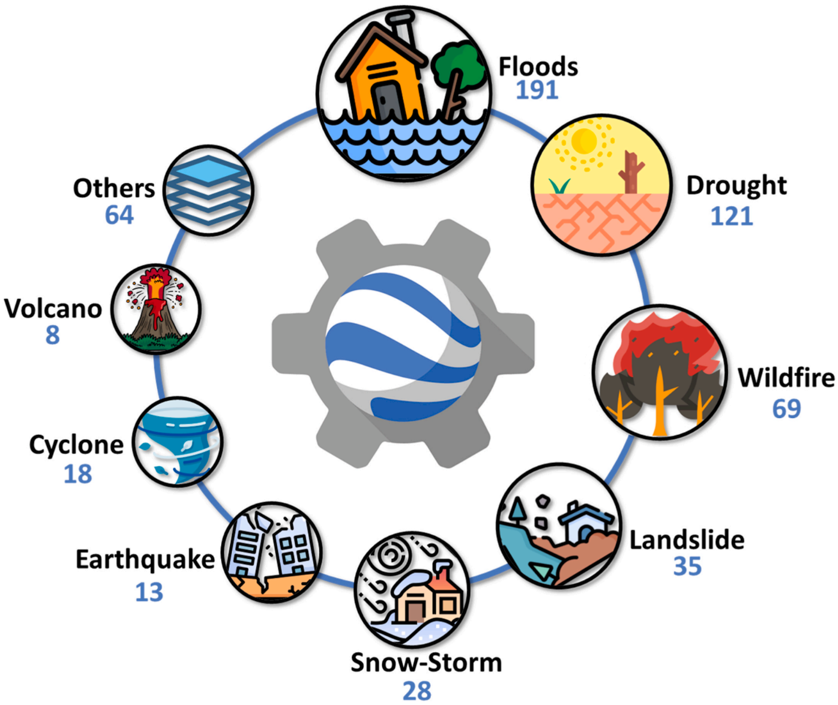
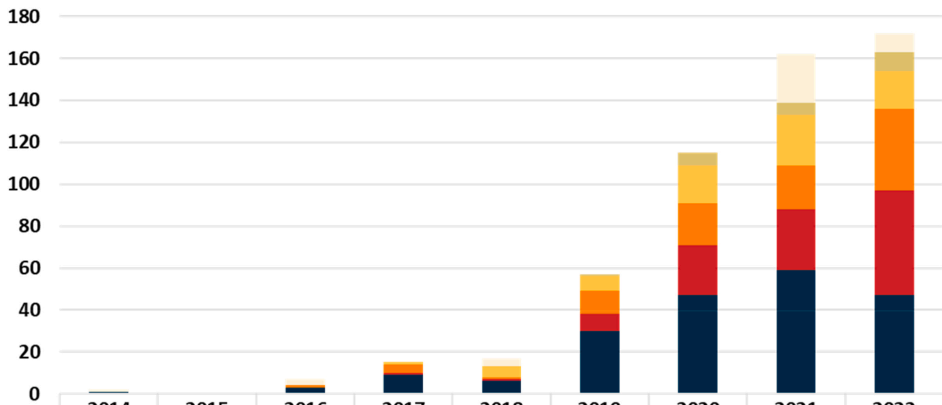


Fig. 4. Categorization of GEE applications in disaster by discipline.



	2014	2015	2016	2017	2018	2019	2020	2021	2022
Other	1	0	3	0	4	0	0	23	9
Optical/SAR	0	0	0	0	0	1	6	6	9
MODIS	0	0	0	1	5	7	18	24	18
Sentinel-1 (SAR)	0	0	1	4	1	11	20	21	39
Sentinel-2	0	0	0	1	1	8	24	29	50
Landsat	1	0	3	9	6	30	47	59	47

Fig. 5. Frequency of studies published on disaster management by utilizing GEE and primary data types per year. Studies are filtered based on database search for the period 2014–2022. No article meeting the given criteria was found prior to 2014.

The first study involving the use of multi-source data was reported in 2019 and now has reached 22 studies combined (2019–2022). This shows that the trend of using multi-source data types in GEE for disaster management applications is still in the initial progressive stage. However, given the ability of this could-based platform in terms of handling multi-source data [40], there are progressive opportunities for advances in disaster management field in the future. When compared side by side, the popularity of Sentinel-2 and Sentinel-1 continued to increase in 2022. In contrast, for Landsat data products, a downward trend is observed similar to MODIS, whose initial study was in 2018, highest 24 studies recorded in 2021, but only 18 studies using MODIS in 2022. Except these, some other data sources, including RADARSAT-1 and 2, Advanced Land Observation Satellite (ALOS), Quick-Bird, WOrldView-

2 and 3, Hyperion, SPOT, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Unmanned Aerial Vehicle (UAV), and AVHRR were grouped into the other category.

3.4. Exploring sources of GEE-based DRM research

3.4.1. Scientific journals as sources

Studies involving the use of GEE for DRM are widely published in various journals of different research fields ranging from natural hazards to remote sensing, thus highlighting the diversity among studies. In most studies, GEE has been used as a primary tool for EOS data acquisition and pre/post-data processing. Fig. 6a shows the top 10 journals' ranking based on citation, among which *Remote Sensing of Environment* and *Remote Sensing* journals ranked top with 2313 and 1861 citations, respectively. Fig. 6b shows the journal's annual production based on article frequency. For 2022, *Remote Sensing* (26) and *ISPRS Archives* (8) journals ranked highest, while for 2021, *Remote Sensing* (27) and *IOP Conference Series: Earth and Environmental Science* (15) ranked highest. It is interesting to note that even though the production of scholarly articles by the journal "*Remote Sensing of Environment* and *Remote Sensing*" is not the highest, its citations are top-ranked—representing its slightly higher acceptance and good reputation among the scientific community. Overall, for the highest article frequency, among 547 articles from 208 journal sources, *Remote Sensing, ISPRS Archives, and Remote Sensing of Environment* ranked top 3 positions with cumulative 89, 28, and 25 published articles respectively.

3.4.2. Geographical distribution of GEE-based DRM research

Country's research output is a term used to quantify the number of times an author of that country has been added as a contributing author in a given duration (either as corresponding or co-author). The evaluation of country-level outputs with respect to a specific topic reflects the awareness of that particular issue among the scholars. Generally, the emergence of scholarly outputs on a specific topic, such as DRM tends to be more prominent in countries where the subject matter is a pressing concern. However, it is important to consider the impact of underdeveloped countries that are also in need of DRM despite having limited publications. For instance, African and South American countries, although highly susceptible to climate-related disasters, face challenges in generating sufficient scholarly output on this topic. A global outlook on country-level research output in DRM and GEE shows that China and USA are ranked the highest. Fig. 7a shows the research output of each country annually, which is the cumulative sum of articles published having corresponding or co-author belonging to that country. Among different countries, the highest output was observed for China (509), USA (377) and India (123) for 2022. It is also evident that the production considerably increased in the last three years,

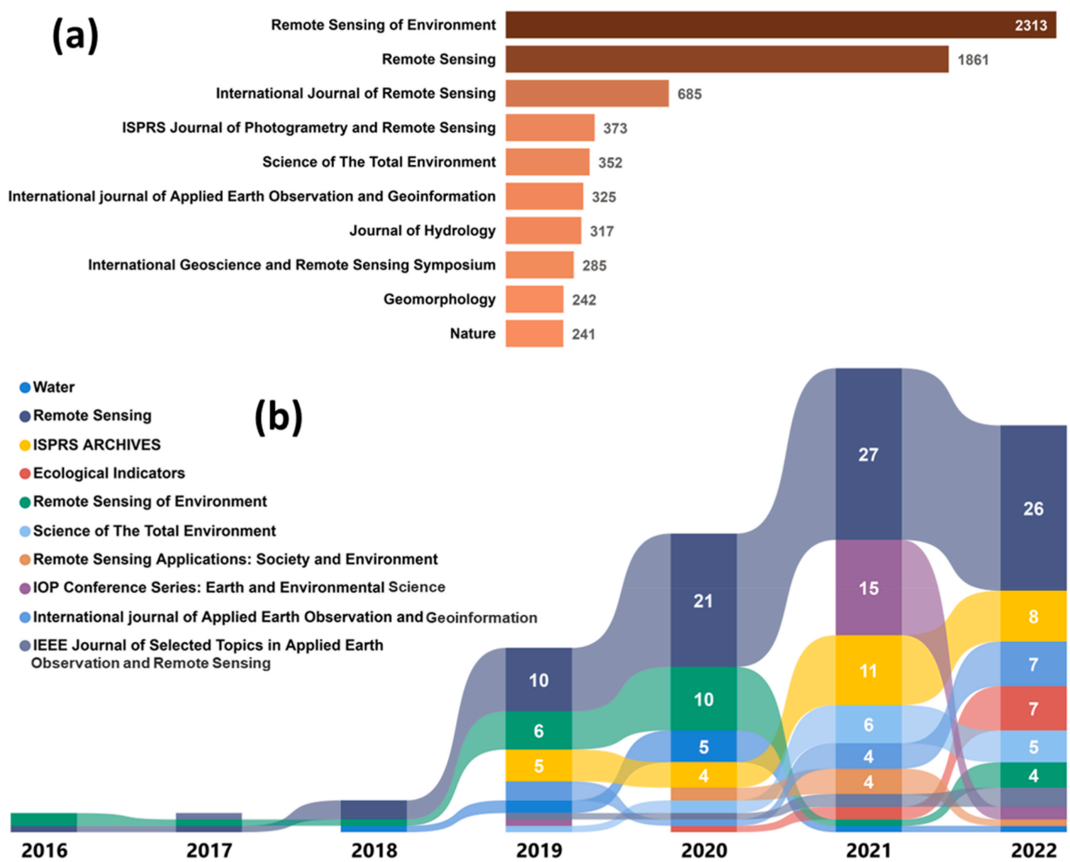


Fig. 6. (a) Most cited journal sources (b) Journals production annually (articles frequency).

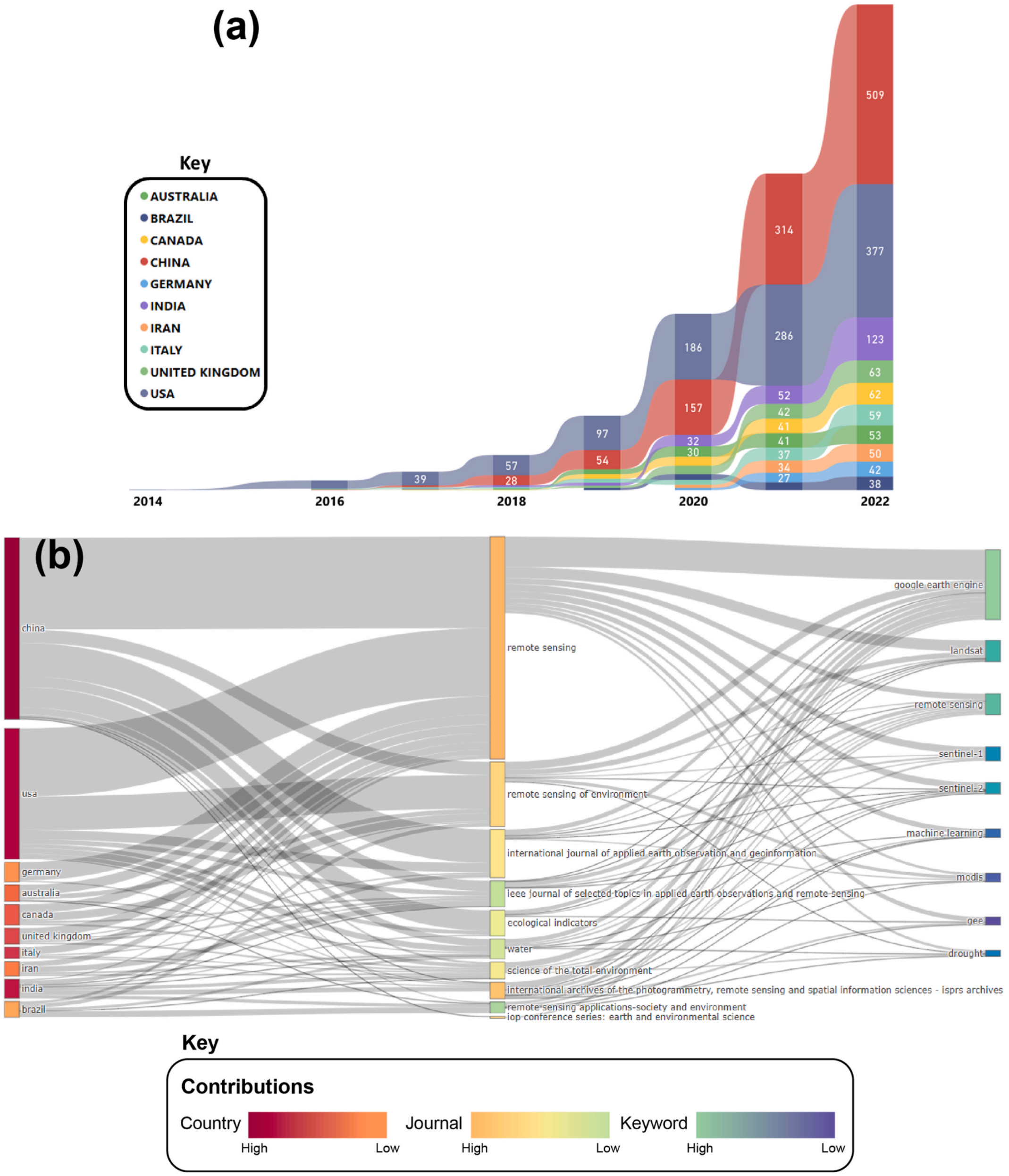


Fig. 7. Countries articles production (corresponding and co-authored) annually (a), and Sankey diagram showing the countries (left) contributing to journals (middle) and then to each author keyword (right).

i.e., China from 157 in 2020 to 509 in 2022. Since these three countries have comparatively more robust economies [41], they support a good working environment, better funding for projects, and higher technological infrastructure, resulting in greater research output in the domain of cloud-based platform integration in DRM-related research [42]. Also, the higher disaster-related damages could also be a driving force in these countries to conduct research in this particular domain using the state-of-the-art tools and technology that can support large-scale assessments and robust exploration of the DRM situation.

To further access the joint collaborative links of different countries, an interconnected network in the form of a Sankey diagram is used, shown in Fig. 7b. The Sankey diagram shows three axes, in which countries (left), journals (middle), and author keywords (right) are shown. Fig. 7b shows that China and USA contributed with the highest studies (wider left red border). Furthermore, the flow links from these countries show that these two countries published majority of their work in Remote Sensing (MDPI), Remote Sensing of Environment (Elsevier), and International Journal of Applied Earth Observation and Geoinformation (Elsevier). These three journals then link to nine research keywords (author defined), including "*google earth engine*", "*landsat*", "*remote sensing*", "*sentinel-1*", "*sentinel-2*", "*machine-learning*", "*modis*", "*gee*", and "*drought*". Furthermore, the flow of China and USA (left axis) links to same journals (middle axis) emphasize the joint collaborative efforts of different researchers in those regions. Given this situation, these two countries can be regarded as highly productive, and with most collaborations in terms of research on DRM and GEE. Further key information on authors and institutions research output is provided in supplementary file under heading "*1.1. Authors and Institutions evaluation*".

In order to assess an individual country's output, the number of published papers only by each corresponding author are analyzed and then visualized to provide a geographical reference, shown in Fig. 8. In general, among the seven continents, Asia published the highest number of papers accounting for 51 % of the total. After Asia, North America and Europe contributed 21 % and 17 %, respectively. Among Asian countries, China (118), India (46), Indonesia (15), and Iran (14) produced the highest share of published studies. For North America, the United States of America (USA) with 80, and Canada with 17 studies stood at the top, whereas in South America, only Brazil accounts for the highest of 10 studies. In Europe, Italy (20), Netherlands (14), and Germany (11) stood as the most prominent countries, whereas in Africa and Oceania, South Africa (8) and Australia (14) ranked highest. To conclude, among different continents, Asia and North America are the most productive whereas among countries, China and USA are the most productive in terms of GEE integration in DRM-related research.

3.5. Knowledge hotspot

Keyword-based ranking techniques were employed to understand the diversity and frequency of the studies investigated in this review (n = 547). A Wordcloud visualization (Fig. 9a) is employed to highlight the most frequent terms based on 100 keywords plus. Among these terms, "*remote sensing*" is the top-used word. Regarding disaster-related keywords, floods and drought are the most prominent, while disaster and risk-assessment are the least occurred words. Overall, the top frequent words observed in this evaluation are *remote sensing, vegetation, engines, google earths, climate-change, floods, drought, and dynamics*. To further explore the situation regarding the used keywords, Fig. 9b shows the Wordtree, which ranks words in descending order based on top 50 keywords plus occurrence (frequency). It is noted that the Wordtree (Fig. 9b) shows similar trends to Worldcloud (Fig. 9a), with remote sensing (85), engines (63), vegetation (62), google earths (53), drought (49), and climate-change (46) to be the highly frequent words. For disaster keywords, drought (49), floods (44), disasters (23), and risk assessment (23) are the highest. Comparatively, based on the keywork plus analysis, it is observed that more studies focused on the applications of GEE to drought monitoring than other hazards.

Keywordco-occurrence link clusters are used to understand the knowledge structure and components of a specific research field by analyzing the potential links in between. For our study, VOSViewer was employed to analyze co-occurrence patterns, and results are shown in Fig. 10. This keywords co-occurrence links analysis resulted into five major research clusters. The first green cluster contains keywords including google earth engine, time series, remote sensing, classification, fire, fire hazard, air quality, and fire degradation. This cluster focuses on fire hazards and their management using GEE with remote sensing techniques and time series analysis. The second (red) cluster contains keywords including remote sensing, rain, hazards, lakes, cloud computing, Mekong River, Yangtze River, and extraction. This cluster theme focuses on applying remote sensing techniques, including extraction (feature extraction)

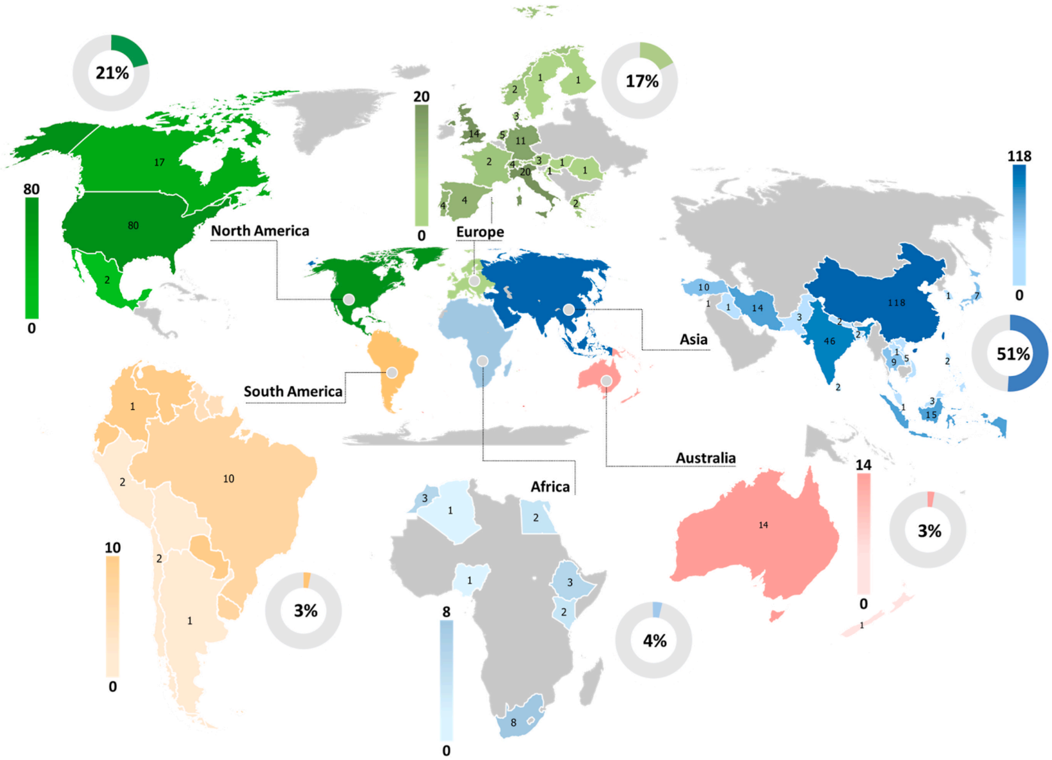


Fig. 8. Country's article (total by the corresponding author's affiliation).

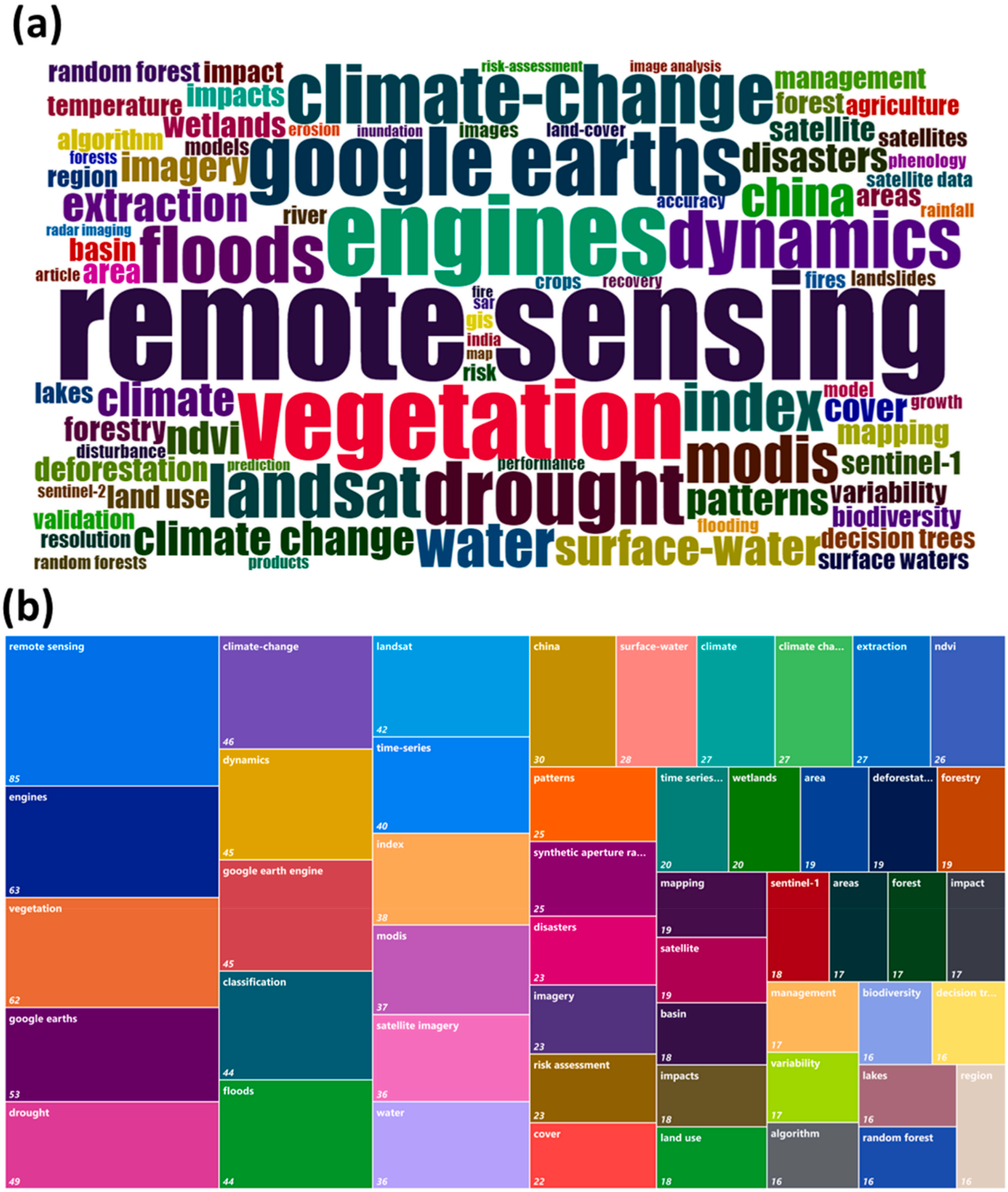


Fig. 9. Wordcloud (A) using 100 keywords plus and Wordtree (b) using 50 keywords plus.

along with cloud computing (GEE), to study lakes and river characteristics. The third (purple) cluster contains floods, synthetic aperture radar, flood control, flood mapping, flood monitoring, mapping, and sentinel-1. This cluster focuses explicitly on flood hazards, with special emphasis on flood control and flood mapping. Besides this, it is also evident that most of the studies on flood hazards use synthetic aperture radar data (Sentinel-1 SAR data) for flood management. The fourth (blue) cluster includes land use, soil moisture, watershed, gis, human, soil survey, and flooding. This cluster highlights the use of land use and soil moisture as a variable in flood hazard assessment. Lastly, the fifth (yellow) cluster contains drought, MODIS, drought stress, and evapotranspiration as the main keywords. This cluster theme suggests that most studies on drought involve studying drought stress through evapotranspiration, mainly using MODIS satellite-based data products. Fig. 10b shows the co-occurrence density of keywords, which justifies Fig. 7a-b as the densest keywords include remote sensing, google earth engine, satellite imagery, floods, drought, and synthetic aperture radar. Fig. 10b further highlights that most studies concentrate on the keywords as mentioned earlier. At the same time, less focus is given to studies including large-scale carbon, forest degradation, fire hazards, forest fire, air quality, and flood monitoring.

To understand the emergence of top research topics, articles are analyzed in terms of the frequency of authors keywords and co-occurrence links on an annual basis. Resulting keyword dynamics are shown in Fig. 13a-b, in which Fig. 11a shows the time series of

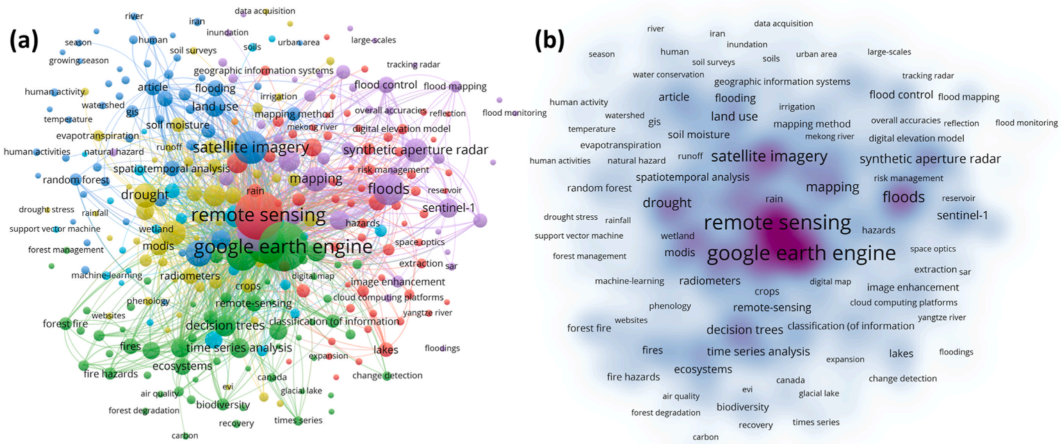


Fig. 10. Keywords co-occurrence links cluster (a) and keywords co-occurrence density (b).

the top ten keyword emergence since 2014. On the other hand, Fig. 11b shows co-occurrence links per year. In Fig. 11a, keyword remote sensing emerged after 2018, where the number of total articles containing that keyword increased from ~15 in 2018 to ~85 in 2022. Similarly, drought and floods keywords continuously increased after 2018, and in 2022 have ~49 and ~44 articles, respectively. In Fig. 11b, keyword co-occurrence shows major keywords (including drought, land-use, and synthetic aperture radar) that emerged after 2019 and are a bit diverse in their scope. For example, land use in 2019 connects to flooding (2020), which then connects to soil moisture (2022). This emergence shows the continuous diversity in major keywords. Other keywords, such as floods (2020), connect to synthetic aperture radar (2019), sentinel-1 (2021), remote sensing (2020), and then to the google earth engine (2021). This time sequence also highlights the advancement in keyword floods which connects to different keywords emphasizing the emergence of remote sensing techniques in different years.

3.6. *Themes, thematic areas, and their evolution*

The thematic evolution flowchart using keywords plus and authors keywords is shown in Fig. 12. Specifically, Fig. 12a shows research themes evolution based on keywords plus from the evaluated studies (n = 547). It is noted that keywords plus are auto generated through a computer algorithm. These are words or phrases that most frequently occur in the reference lists of a research paper. In Fig. 12a, fourteen themes are presented on the left axis for the period 2014–2019, whereas two themes are shown for the 2020–2022 duration on the right axis. Among the left axis themes, *remote sensing, agriculture, wetlands, vegetation, and products* emerged as a general theme *remote sensing* (right side) in recent years (i.e., 2020–2022). Other than these, *random forest, system, cover, climate-change, index, validation, model, runoff, and california* were linked to the *vegetation* theme on the right side in 2020–2022. In Fig. 12b, the flow is based on the authors keywords, in which fifteen themes from the left axis (2014–2019) are linked to eight themes on the right (2020–2022). Themes such as *climate change, gis, agriculture, and google earth engine* are linked to *drought*. Other themes, including *big data, change detection, cloud computing, phenology, time series, land cover changes, and sentinel-1* are linked to the central theme *google earth engine*. Similarly, the last four left-side themes, including *earth engine, landsat 8, inundation and glacial lake,* are linked to diverse themes on the right sides such as *google, glacial lake, landsat-8, google earth, land use change, and dongting lake*. Here, it is worth mentioning that theme keywords such as *google, google earth, earth engine, and google earth engine*, all represent the same word, GEE, but are placed in different themes by software.

The results of cluster analysis using authors, sources, and thematic evolution keywords are presented in Fig. 13. In general, each cluster analysis graph in Fig. 13 is divided into four zones, where each thematic quadrant zone represents a specific research theme. In Fig. 13a, the thematic map is based on authors, in which the left and right axis represents impact and centrality, respectively. In contrast, the inner circle contains keywords and their respective weightage percentage. The top-right quadrant (motor themes) of Fig. 13a represents high impact and high centrality. It is regarded as the quadrant with trending topics in the chosen research field (i.e., DRM and GEE). This quadrant contains three distinct research themes: the first theme with *floods, dynamics, and algorithms*; the second theme with *Canada, direct carbon emissions, and forest-fires*; and the last theme with *classification, imagery, and models* as trending topics. Contrarily, the top-left quadrant (niche themes) visualizes two themes, showing high impact and low centrality (i.e., high development topics). It includes keywords such as *patterns, index,* and *climate* as the first theme, whereas *drought, climate-change, and remote sensing* as the second theme. Similarly, the bottom-right quadrant (basic themes) visualizes two themes with low impact and high centrality (i.e., general topics that are discussed frequently in this particular domain). In this quadrant, the first theme includes *classification, dynamics*, and *china,* whereas the latter contains *leaf-area index*, *maize,* and *modis* as research keywords. Lastly, the bottom-left quadrant (declining themes) depicts low impact and low centrality and includes topics that have been used in the past but are no longer used or are diminishing from the research field. This quadrant contains three themes: first one with water, china, and classification; second with lava flows, mapping, and remote sensing; and the last with *susceptibility, climate,* and *erosion* as keywords.

Fig. 13b shows the thematic evolution of research keywords clusters based on keywords plus. The top-right quadrant visualizes six themes, with main keywords such as remote sensing, vegetation, wetlands, agriculture, climate-change, and index: thus highlighting

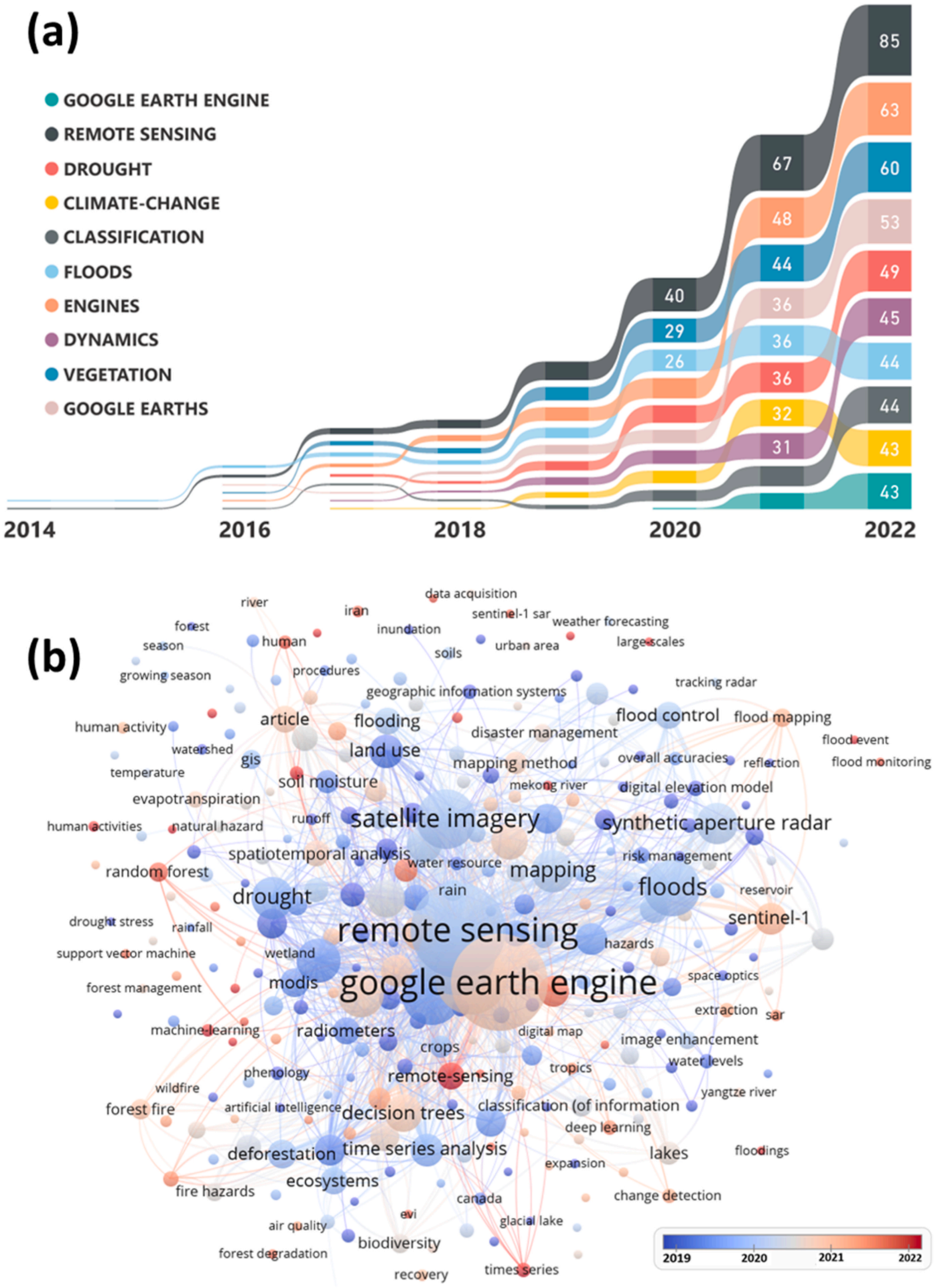


Fig. 11. Trending topics in disaster risk assessment and GEE (a) and annual co-occurrence map of keywords (b).

high development and high relevance. The top-left quadrant visualizes three themes, first theme with keywords including canda, direct carbon emission, forest-fires, second theme with keywords including three-dimensional computer graphics and visualization, and the last theme with topics including California and models. The bottom-right quadrant contains three themes, two with keywords including cover, dynamics, time series, products satellite and dnbr, whereas for shared one keywords include runoff, evapotranspiration, and remote-sensing data. Lastly, the bottom-left quadrant visualizes six themes, in which two themes shared axis with niche and basic themes. In this quadrant, keywords include model, streamflow, moisture, random forest, validation, and retrievals. To summa-

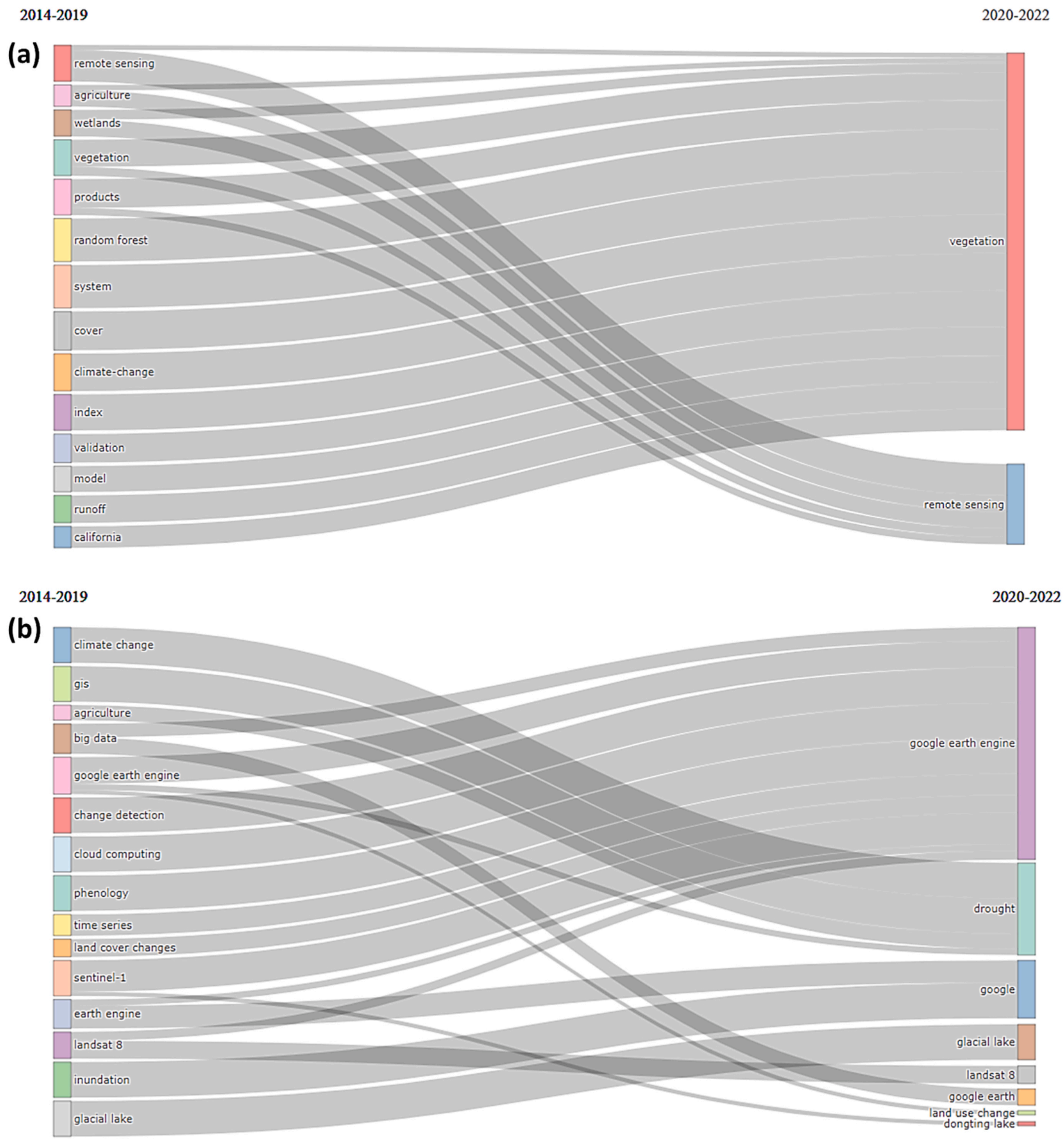


Fig. 12. Thematic evolution based on (a) keywords plus, and (b) authors keywords.

rize, from the perspective of application of GEE in the field of DRM, Fig. 13b highlights that the topics in the top right quadrant (i.e., flood using remote sensing and engines) should be further explored as they showed high degree of development along with centrality.

Factorial analysis, a statistical-based method, is used to quantify variability among observed correlated variables. This technique, along with Multiple Correspondence Analysis (MCA), is used to observe the relationship between two or more qualitative variables [43]. As a graphical technique, MCA reduces the distance between connecting points in a graph, forming clusters, as shown in Fig. 14a. From the conceptual map of factorial analysis using MCA (Fig. 14a), two distinct themes are observed, categorized as cluster 1 (blue-colored) and cluster 2 (red-colored). The keywords in factorial analysis collate directly with previous keywords occurrence cluster (Figs. 11 and 12) and represent emerging research clusters as individual clusters. In general, cluster 1 signifies 30 keywords, whereas cluster 2 signifies 18. In cluster 1, keywords include *ndvi, extraction, climate change, surface water, basin, classification, random forest, areas, imagery, management, area, region, variability, time series, patterns, cover, index, impacts, satellite, water, impacts, satellite, water, impact, dynamics, china, forest, climate, temperature, vegetation, modis, drought,* and *algorithm*. In cluster 2, keywords include *google earth engine, disasters, sentinel-1, mapping, decision tree, google earths, synthetic aperture radar, remote sensing, engines, floods, risk assessment, deforestation, time series, forestry, landsat, satellite imagery, climate change,* and *wetlands*.

To further analyze the emergence of research themes, keywords found in factorial analysis (Fig. 14a) are visualized as a dendrogram shown in Fig. 14b. A dendrogram is a type of diagram that shows the relationships of keywords in the form of hierarchical clusters using branches called clades and the endpoint of each clade called a leaf [38]. Since in bibliometric analysis, dendrogram shows the hierarchical relationship between topics, they are often termed as hierarchical clustering diagram. The height of Fig. 14b repre-

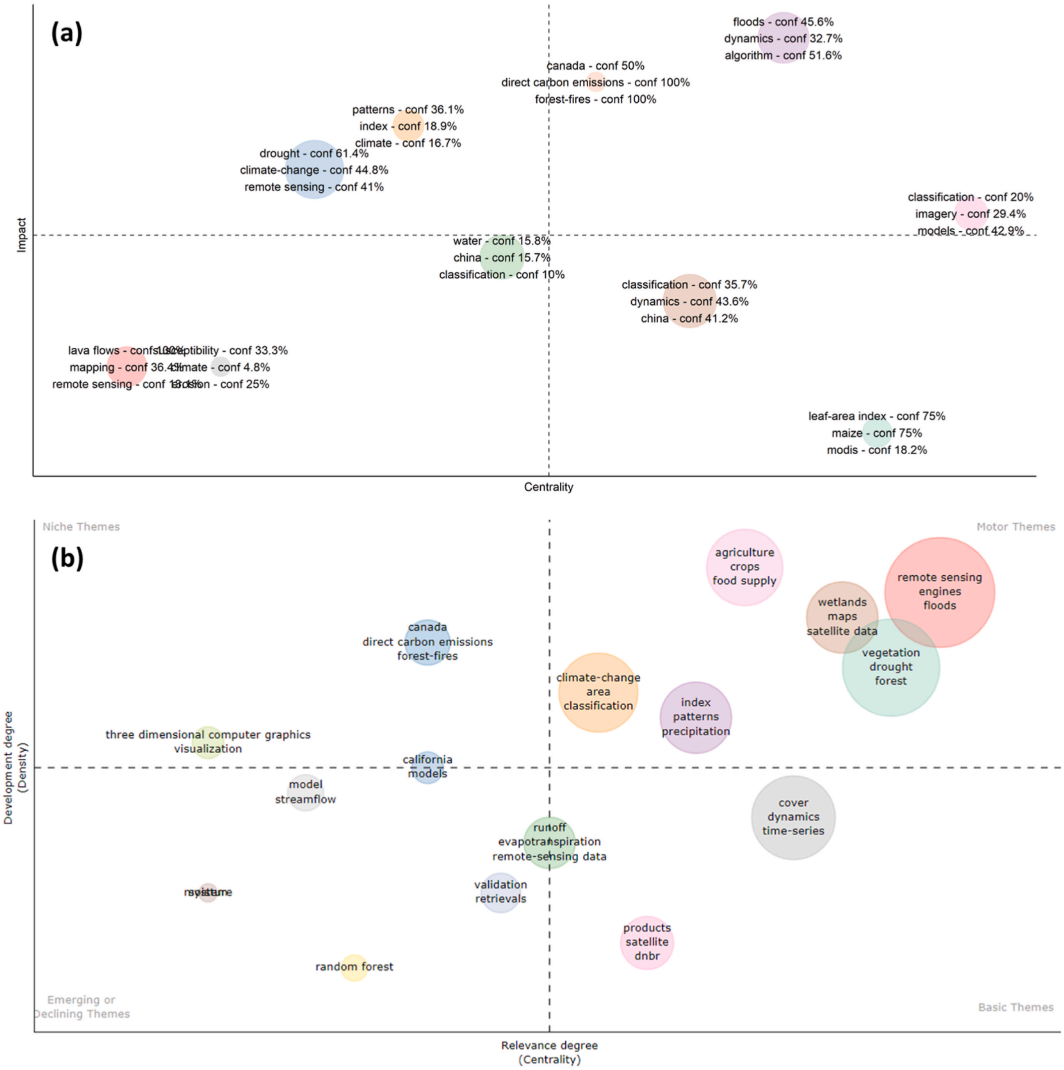


Fig. 13. Clustering based on (a) authors, (b) keywords plus (sources), and (c) thematic evolution using keywords plus.

sents the similarity strength between the two topics. In cluster 1, the most critical research theme relations include surface water with basin, classification with random forest, index with impacts, water with impacts, climate with temperature, and drought with algorithm. Notably, cluster 1 also highlights the keyword *ndvi* to be highest in relationship with other research themes of cluster 1. This situation signifies the role of NDVI as an important variable in various research themes, i.e., drought, vegetation, climate change, and forest.

Cluster 2 shows google earth engine and disaster to be the most critical research theme. Other significant research themes included engines with flood, risk assessment with deforestation, and climate change with wetlands. Specifically, the relationship between GEE and disaster is more prominent with its neighboring leaves including sentinel-1, mapping, and decision trees. This relationship implies that the GEE application in disaster currently focuses more on using Sentinel-1 satellite imagery for mapping through decision tree-based models (i.e., Random Forest). Similarly, this relationship can also be observed in the following clades in which google earths keyword is directly linked to synthetic aperture radar (the data type of Sentinel-1).

Regarding specific hazards, the relation of keyword engines (i.e., GEE) with flood is observed but with minimal relationship strength, implying comparatively low research progress in this field. Besides, the association of keyword risk assessment with deforestation is prominent, which can also be observed in later relationships in which time series analysis directly links to forestry. These two links imply that the risk assessment mainly focuses more on the deforestation phenomenon, with time series being an effective technique to analyze the changes. Lastly, the keyword *landsat* emerges with *satellite imagery, climate change*, and *wetlands*, implying that besides Sentinel-1, Landsat is also explicitly used for analyzing climate change-related impacts using GEE.

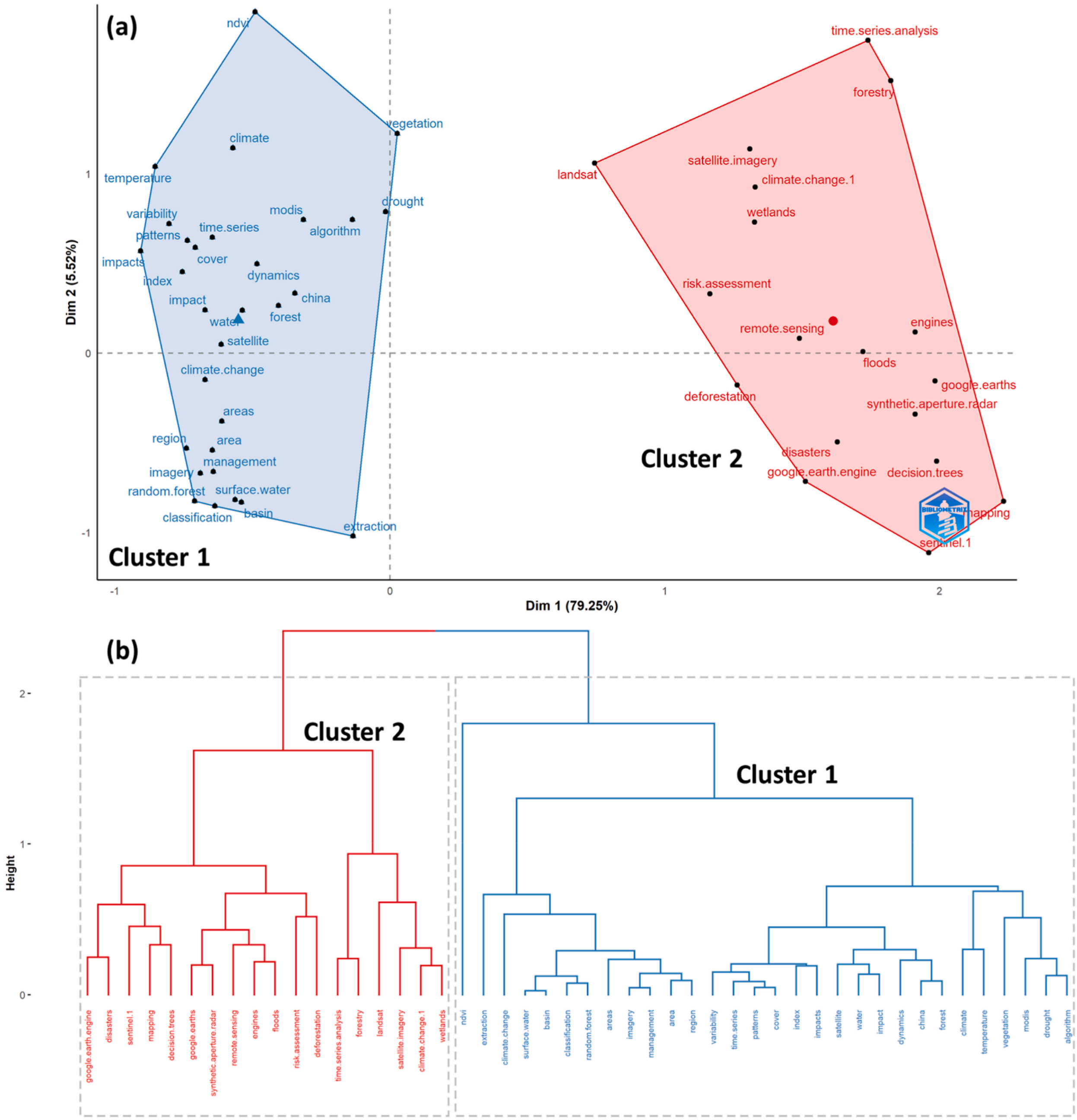


Fig. 14. Factorial Analysis using multiple correspondence analysis shows as (a) conceptual map and (b) topic dendrogram.

4. Conclusions and the way-forward

Over the past few years, GEE has emerged as a major could computing-based platform for robust multi scale (e.g., planetary, regional, national, and local scales) geo bigdata analyses, with applications in different fields, including DRM (assessment, profiling, monitoring, and planning etc.). The present study evaluated 547 studies and confirmed the emergence of GEE in the field of remote sensing applications, particularly its utilization in disaster management. Based on the comprehensive and systematic review provided above, this study concludes the following:

a) Among hazard types, most researchers use GEE for flood, drought, and wildfire assessments, with 191 (35 %), 121 (22 %), and 69 (13 %) studies published, respectively. For the flood category, many studies use GEE for rapid flood assessment, using Sentinel-1 SAR data, freely available in the GEE data catalog. Besides, GEE was used to its full potential in many cases, which focused on preparing web-based applications for on-time flood assessment and emergency response systems using GEE processing platform and data from GEE data catalog (i.e., GEE4FlOOD and FPERS). Other studies used GEE for flood risk evaluation on the specific land-use type (i.e., cropland) and urban infrastructure. Moreover, some studies also emphasized flood susceptibility analysis powered by GEE in high flood zone areas. Besides flood hazard, GEE applications in droughts are observed, which focuses specifically on drought explorations such as drought monitoring using drought severity index (DSI) and temperature-vegetation-soil moisture-precipitation drought index (TVMPDI), drought impact assessment, and the use of satellite-derived ready to use products, (i.e., from MODIS and Landsat based indices) for drought assessment. After the drought, most of the work was observed for wildfire hazards, including wildfire damage assessment, susceptibility analysis, analyzing the global carbon cycle because of global wildfires, studying afforestation, and analyzing the change in vegetation health because of wildfire incidents.

b) GEE applications, particularly in disaster management, showed exponential growth since the launch of this platform in 2010. For instance, 60 studies were published in 2019, whereas 170 were published in 2022, resulting in an increase of ~183 % between 2019 and 2022. Research production of a country is observed using co-authored papers, for which most of the productive work is contributed by Asian and North American countries, particularly China with 509 co-authored papers, the United States of America (USA) with 377 co-authored papers, and India with 123 co-authored papers. Regarding the number of publications published by either first or corresponding author, again China, USA, and India are among the countries ranked top with 118, 80, and 46 publications, respectively. In terms of institutional productivity, the University of Chinese Academy of Sciences (UCAS) and its sub-institutes contributed the highest research outputs, particularly in collaboration with the universities from the USA. Top-ranked journals (per citations) include Remote Sensing of Environment, Remote Sensing, and International Journal of Remote Sensing.

c) In our comprehensive review of 547 studies on GEE for DRM, we found that most researchers favored optical datasets such as Landsat and Sentinel-2. Some also utilized Sentinel-1 SAR datasets for hazard impact assessment, particularly in flood-related applications like flood damage assessment. An interesting trend emerged with the increasing use of multi-source datasets combining optical and SAR data, which gained momentum after 2020. However, only a few studies preferred coarser resolution satellite datasets like MODIS for disaster management research. While these datasets offer broader coverage, they may lack fine-scale details. Our findings highlight the widespread use of optical datasets and the growing recognition of SAR data's value in disaster management. The trend of combining multi-source datasets opens new avenues for future research, but further exploration of coarser resolution satellite datasets is encouraged to fully understand their potential in advancing disaster management.

d) Trending topics in the analyzed 547 studies include google earth engine, remote sensing, drought, and floods. The keyword *Google Earth Engine* includes further sub-keywords, i.e., google earths, engines, and GEE, and therefore was considered one. Regarding hazards, keywords related to drought and floods were the most prominent, followed by techniques including classification, time series, index, risk assessment, and data type as SAR. In terms of keywords emergence, vegetation and remote sensing emerged during 2014–2020, whereas, google earth engine, drought, glacial lake, landsat 8, and land use change, in the recent years (i.e., 2020–2022). The cluster-based analysis highlighted core development areas, including remote sensing, vegetation, wetlands, agriculture, climate-change, and index. These areas showed the highest development with the highest relevance to the proposed topic, i.e., GEE applications in DRM.

e) Lastly, through factorial analysis, conceptual maps highlighted that google earth engines with disaster is the most critical research theme in most of the studies.

Regarding future research significance, this study highlights three research themes groups, including (1) GEE with flood, (2) risk assessment with deforestation, and (3) (3) climate change with wetlands. Additionally, it is noted that several research gaps still exist in relation to climate change and extreme event scenarios. These gaps include the need for further development of sophisticated models integrating climate change projections with geospatial data, the integration of real-time data and predictive analytics within platforms, and the inclusion of local knowledge and community engagement for more effective strategies in the face of climate-related risks. Furthermore, regarding specific hazards, a relation of GEE with floods was more dominant than other hazards implying the activeness of researchers working on this research domain. The findings of this study could be helpful for early-stage researchers focusing on DRM using GEE. The cluster (Fig. 13) and Factorial analyses (Fig. 14) signify that flood hazards have a high impact, development, and centrality for this core topic of DRM with GEE. Specifically, the emphasis is on using remote sensing techniques, GEE as a processing platform, and various algorithms (i.e., machine learning and deep learning) for flood hazard mapping, susceptibility evaluation, and risk assessment. Lastly, while much of the research emergence is noticed for flood hazard, there are still areas of further consideration, including three-dimensional data processing techniques, classification using different ML and DL models, use of other sensors' data (i.e., Sentinel-1) for rapid flood assessment, and early warning systems aided by GEE and earth observational datasets. Also, there is a lack of interactive platforms to perform near-real-time flood situation analysis, which is a potential research direction for upcoming studies as it is imperative for early resources deployment to reduce the disaster impacts.

While the advancement in the field of DRM and cloud computing is provided in this review, future studies can focus on the utilization of GEE for studying compound disasters, which is also one of the limited areas of research when it comes to GEE applications. Although considerable work is being carried out in the field of compound hazards and multi-hazard risks [44], there is still a gap in terms of international collaboration and conducting such assessments on regional to global scales including cross-border perspectives. GEE offers promising capabilities to study compound disasters for effective DRM on larger scales due to its powerful ability to process and analyze multi-source data [45]. Specifically, GEE enables (a) data integration and analysis, (b) real-time monitoring and early warning systems, (c) modelling and simulation, (d) visualization and communication, as well as (e) collaboration and knowledge sharing [46]. Therefore, by leveraging the freely accessible vast datasets of satellite imagery and geospatial data, researchers can gain insights into the multiple hazards involved in compound disasters, assess vulnerabilities, predict impacts, and develop proactive strategies. Lastly, GEE facilitates the integration of various data sources, enables near-real-time disaster monitoring, supports complex modelling, provides visualization tools, and fosters collaboration among stakeholders for effective DRM.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All the data used for this study is available freely and the resources are mentioned in the article

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Appendix A. Supplementary data

Supplementary data to this article can be found online at.https://doi.org/10.1016/j.ijdrr.2023.104056.

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