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What is going on within google earth engine? A systematic review and meta-analysis

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ABSTRACT

Google Earth Engine (GEE) is a geospatial processing platform based on geo-information applications in the 'cloud'. This platform provides free access to huge volumes of satellite data for computing, and offers support tools to monitor and analyse environmental features on a large scale. Such facilities have been widely used in numerous studies about land management and planning. Considering the current lack of relevant overviews, it may be useful to evaluate the utilization paths of GEE and its impact on the scientific community. For this purpose, a systematic review has been conducted using the PRISMA methodology based on 343 articles published from 2020 to 2022 in high-impact scientific journals, selected from the Scopus and Google Scholar databases. After an overview of the publishing context, an analysis of the frequency of satellite features, processing methods, applications are carried out, and a special attention is given to the COVID-19 studies. Finally, the geographical distribution of the reviewed articles is evaluated, and the citation impact metrics is analysed. On a bibliometric approach, 90 journals published articles on GEE in the reference period (January 2020 to April 2022), and this large number of journals reveals the multidisciplinary application of GEE platform as well as the interest of publishers towards this topic of relevance for the international scientific community. The results of the meta-analysis following the systematic review showed that: (i) the Landsat 8 was the most widely-used satellite (25%); (i) the non-parametric classification methods, mainly Random Forest, were the most recurrent algorithms (31%); and (iii) the water resources assessment and prediction were the most common methodological applications (22%). A low number of articles about COVID-19, in spite of the planetary importance of the pandemic effects. The reviewed articles were geographically distributed among 86 countries, China, United States, and India accounting for the large number. 'Remote Sensing' and 'Remote Sensing of Environment' were the leading journals in the citation impact metrics, while the Random Forest method and the agriculture-related applications being the mostly cited. It is expected that these results might change over the mid to long term, due to fast progress in environmental and spatial information technologies, although currently our findings may be worthwhile and useful for assessing the current global deployment of GEE platform.

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1. Introduction

Geographical science mainly focuses on the interaction of physical and human factors based on their relations as well as their spatio-temporal distribution on the Earth's surface. Due to this holistic approach, many authors consider the geographical science as an adequate field to study global environmental processes (Goodchild, 2013). The role of Geographic Information Systems (GIS) for data collection in geographical science is essential, since these systems are useful tools that allow easy and quick acquisition and processing of basic information, especially on environmental processes related to soil, vegetation and water (Chang, 2019). In this framework, remote sensing (RS) provides a huge amount of information collected on global scales and captured by different satellite sensors. The availability of further open access datasets from remote sensing, and the extremely quick advancement of sensor technologies are increasing (Lin et al., 2018). Thus, unexpectedly, RS-based studies have not been limited by a lack of information, but by the impossibility of analysing the large amount of available data (Yang et al., 2017).

The massive collection of information, known as 'big data', was first introduced in the mid-1990s by the scientific community (Li et al., 2016), which refers to a large amount of data that are not easy to be processed, stored and managed using conventional computing tools (Liu, 2015). Big data is mainly characterised by volume, variety and velocity, defined by its attributes as three dimensions (Laney, 2001). To truly comprehend the relevance of the power of data in RS, it is necessary to extract the hidden quality of the information, by bringing together three perspectives: access to data, applications of data and data methods (Chi et al., 2016). The management of big data in RS opens new but sometime difficult challenges, such as the massive and complex data storage, intensive and irregular data access patterns, management of RS "Big Data" in the multilevel memory hierarchy, optimal scheduling of a large set of dependent tasks, in addition to efficient scheduling of RS applications (Ma et al., 2015).

Nowadays, major geo-big data analytics are developing on cloud platforms, since these platforms provides more accessibility and affordability, using flexible processors, memory and disk size. In particular, cloud computing provides storage for keeping big data with affordable scalability. Moreover, these cloud computing systems offer infrastructure, platform, storage and software as on-demand services (Sun and Scanlon, 2019). Among these cloud computing services, Google Earth Engine (GEE) stands out. GEE allows an analysis-ready data catalogue of several petabytes, combined with an inherently parallel, high-performance computational service. Using an application programming interface (API), it is controlled, accessible via Internet, and an associated web-based interactive development environment (IDE), which supports fast prototyping and visualisation of results (Gorelick et al., 2017).

Despite its current limitations (Gorelick et al., 2017), GEE has certainly become the most widely-spread cloud processing tool nowadays, providing a crucial role for geographical big data analysis in RS (Tamiminia et al., 2020). Many elements integrate the architecture of the GEE, but RS information and operations functions are essential. To begin with, GEE offers an impressive number of datasets, both raw data and pre-processed data, and products that are available at any scale (global, national and local). It is an extensive library of satellite images collected over the last 40 years from the main sensors of land monitoring programmes such as Landsat, MODIS, NOAA, Sentinel or ALOS, among other datasets (Gorelick et al., 2017). Furthermore, GEE provides climate, meteorological and geophysical datasets to be used as inputs for several models or applications, updated on a daily basis and instantly available for analysis. Finally, GE offers the capability to use both the information available on the platform and own data as well as to operate with own and platform data in a combined way (Amani et al., 2020a).

Concerning the operational functions, GEE allows spectral and spatial analyses to be applied to batches of imagery. These calculations can be simple mathematical operations or advanced image processing and machine learning algorithms, based on a library of application programming interfaces (APIs) development environments that support common coding languages, such as JavaScript or Python (Tamiminia et al., 2020). Both supervised and unsupervised machine learning algorithms can be applied through the platform's image catalogue (Jinxiaet al., 2022). The latter provides a suite of classifier algorithms, such as Random Forest (RF) (Magidi et al., 2021), Support Vector Machine (SVM) (Awad, 2021) or Classification and Regression Tree (CART) (Chen, H. et al., 2022) as well as supervised classification methods (Amani et al., 2019; Hasan et al., 2022). Popular clustering algorithms such as K-Means, Cobweb or Simple Non-Iterative Clustering (SNIC) are also available (Gorelick et al., 2017). However, GEE provides fewer spatial functions due to parallel implementation problems, making the program filtering techniques (Gaussian and Laplacian, Sobel, Hough transform) a complex task. However, GEE does not support functions from FFT Wavelet algorithms, hierarchical algorithms or physics-based models, and therefore these developments are suggested as future challenges (Amani et al., 2020a).

Several authors have explored the significant research outputs related to the use of the GEE platform, revealing the tip of the iceberg regarding the potential developments provided by cloud processing platforms (Gorelick et al., 2017; Amani et al., 2020a; Tamiminia et al., 2020). The scientific literature shows a wide spectrum of applications in environmental analyses on both regional and global scales. Moreover, more studies were found applying RS datasets compared to articles employing ready-to-use products, and the most used image set has been Landsat satellite optical imagery (Amani et al., 2020a). Among the ready-to-use products, the normalised difference vegetation index (NDVI) was used in 27% of the studies for vegetation, crops, land cover mapping and drought monitoring. Furthermore, linear regression and random forest were the most commonly used algorithms for satellite image processing (Tamiminia et al., 2020).

The impact of GEE on geospatial data science community has been exponential since its release in 2010. More research papers have been published in the recent two years and a half compared to the decade since GEE has been in use. Therefore, the need for a new analysis is convenient, in order to provide a summary of the state of the art. This paper aims to propose an updated and systematic review related to the use and application of the GEE platform, using the criteria of the PRISMA 2020 statement and based on articles published from 2020 to present on impact journals. The specific objectives are: (i) to identify some questions that could not be solved in individual studies; (ii) to find future priorities for further exploration; (iii) to address potential problems that may have arisen in previous research.

2. Materials and methods

The Elsevier's Scopus (www.scopus.com) and Google Scholar (scholar.google.com) databases were used to perform the bibliometric analysis by searching for articles relevant to the topic. The reference period was 1 January 2020 to 1 May 2022 (hereafter referred to as 'present'), which allowed us a comparison of the results obtained by Tamiminia et al. (2020) from 2013 to 2019. The criteria to identify the relevant articles were: (i) the exclusive presence of the term "Google Earth Engine" in the title; (ii) the English language; and (iii) the publication on impact journals. The query string used in the "Scopus advanced document search" application was: "*TITLE ("Google Earth Engine") AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT- TO (PUBYEAR, 2020)) AND (LIMIT-TO (LANGUAGE, "English"))*". A very similar identification criterion was set in the Google Scholar database.

After the identification of the relevant papers, the study applied the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020 statement) (Page et al., 2021), in order to select the articles to be included in the quantitative synthesis ('meta-analysis'). Two different blocks of information were collected in the database. The first block included the qualitative values of the journals and scientific articles screened (year of publication, DOI, keywords, citations, Journal Impact IF Ranking and publication fee), which served to characterise the publication context. A second set of information that was related to the content of the articles (study area or country, study size, satellite, sensor type, resolution, application and computing analysis method) was extracted, which provided a major input for the meta-analysis.

3. Results and discussion

Firstly, it should be noted that more research has been carried out using the GEE platform than the articles analysed in this review. To pay attention only in a Scopus search, 1753 research articles, reviewed within the study period, used "Google Earth Engine" anywhere in the title, abstract or keywords. After a careful analysis, we realized that the use of GEE platform was not the main focus of most of these studies. Therefore, a list of 1210 articles extracted from the databases of Google Scholar (n = 853) and Scopus (n = 357), and containing the term 'Google Earth Engine' exclusively in the title was retained, which indicated an implicit use of the platform in the core of the research (Fig. 1).

The 1210 papers were reduced to 439, by removing duplicities between the two databases. Of the articles removed from the Google database, 416 were not written in English. Finally, 12 full-text articles that were not published in impact journals were also excluded. The studies that were eligible for the qualitative synthesis were therefore 343, of which 337 were included in the quantitative synthesis (meta-analysis).

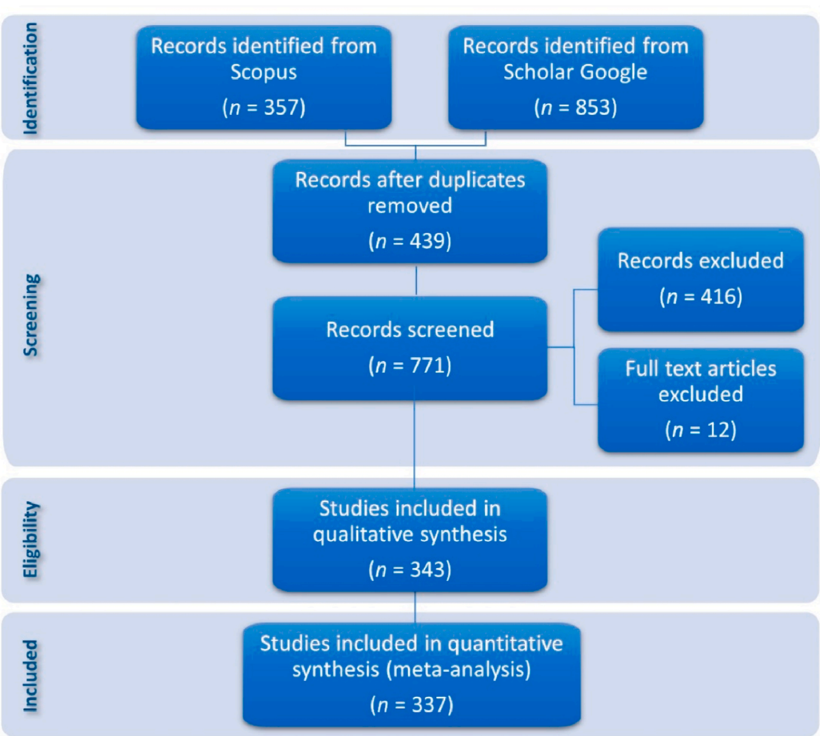


Fig. 1. PRISMA 2020-based flowchart on the article selection process.

3.1. Bibliometric analysis

A review within the current context of international scientific journals related to the studies using GEE platform is worthwhile to better understand the publishers' framework. A total of 90 journals published the 343 articles focusing on GEE in the reference period, and this number is noticeably lower compared to the period 2013 to 2019 (124 journals) (Taminia et al., 2020). Such a high number of journals reveals the interest of publishers in a topic of this importance for the scientific community. In addition, it should be highlighted that the increase, from 2.3% to 5%, of journals publishing at least 5 articles as well as the reduction of journals with only one article, from 35.5% to 17.2%.

Despite the high number of journals publishing articles on GEE, a clear concentration of the analysed papers in a few journals can be observed (Table 1). 'Remote Sensing' and 'Remote Sensing of Environment' were classified at the first and second rank (together 259 articles), with 'Remote Sensing' showing a contribute of almost a third of the published articles.

Within the reference period, 323 (94.2% of the total) articles are included in the top publishers (see Table 2), of which MDPI and Elsevier published 152 (44.3%) and 80 articles (23.3%), respectively (Table 2). It is worth noting that MDPI, despite holding about half journals compared to Elsevier, published almost twice articles. This finding reveals the magnitude and impact of open access journals on the dissemination of articles on GEE, which provides an important research resource for developing countries. Broadly considered, the open access journals contributed to 59.2% of the examined articles compared to 40.8% of subscription journals. In this scenario, MDPI becomes the leading publisher, publishing 44.3% of the total articles and 74.9% of the open access articles.

A further interesting issue is the quality of the published articles, based on the ranking values of the journals published by the Journal Impact Factor 2021 retrieved from Clarivate Analytics (2018). Among the total published articles, 63.8% were in the first quartile (Q1) journals, and this percentage becomes 91.8% if referred to the first and second (Q2) quartiles (Table 2). In this case, MDPI and Elservier published 52.2% and 67.1% of these articles, respectively. In short, these results show the noticeable level of the studies in the last few years, which confirms the usefulness and applicability of the GEE platform as a research tool for scientists.

3.2. Review of articles on GEE

Scientific research on published articles about GEE has been steadily increasing since the release of the GEE platform in 2010 (Fig. 2). Evidently, as many articles have been published in the last two years and a half as during a decade, largely due to the widespread popularity of this cloud platform (Gorelick et al., 2017). The first four months of 2022 alone show an increasing trend, since 56 articles using the GEE platform as a core research tool have been identified, which is higher compared to the same period in 2021. (Fig. 2).

The analysis of the main topics of research through the key words included in the articles reveals interesting considerations. The keyword review provided 1868 different terms. The subsequent analysis shows that the most commonly used definition in the keywords was 'Google Earth Engine'. In Fig. 3, rectangles sizes show the frequency of occurrence of keywords in the reviewed articles. In

Table 1
Number of published articles on GEE per journal.

Journals	2013-2019	2020-2022	Total	% on the total
Remote Sensing	96	109	205	29.6
Remote Sensing of Environment	43	11	54	7.8
ISPRS-J. Photogramm. *Remote Sensing*	8	14	22	3.2
IEEE J. Sel. Top. Appl. Earth Observ. *Remote Sensing*	5	16	21	3.0
Int. J. Appl. Earth Obs. Geoinf.	13	6	19	2.7
International Journal of Remote Sensing	8	7	15	2.2
PLoS ONE	9	4	13	1.9
Science of the Total Environment	5	3	8	1.2
Other journals	162	173	335	48.4
TOTAL	**349**	**343**	**692**	**100**

Note: Values from 2013 to 2019 extracted from Taminia et al. (2020)..

Table 2
Distribution of the journals and articles on GEE among their publishers according to the publication quality.

Publisher	Journals	Articles	Q1	Q2	Q3	Q4
MDPI	12	152	117	33	2	–
Elsevier	26	80	62	18	–	–
Taylor & Francis	11	32	8	19	5	–
Springer	15	26	1	10	14	1
IEEE	4	22	21	1	–	–
Wiley	6	6	3	3	–	–
Copernicus G.	4	5	5	–	–	–
Other publishers	13	20	2	12	3,0	3
TOTAL	**91**	**343**	**219**	**96**	**24**	**4**

Note: Quartile data sourced from Clarivate Analytics. Rank by Journal Impact Factor 2021. Publisher acronyms: Multidisciplinary Digital Publishing Institute (MDPI); IEEE-Inst Electrical Electronics Engineers Inc (IEEE); Copernicus Gesellschaft (Copernicus G.).

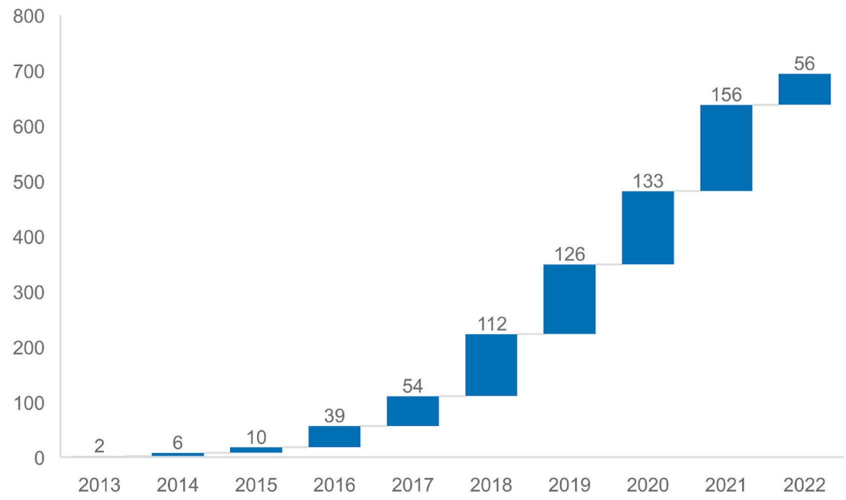


Fig. 2. Cumulative value of GEE articles publications per year. Values from 2013 to 2019 extracted from Tamiminia et al. (2020). Values from 2022 extracted until 1 May.

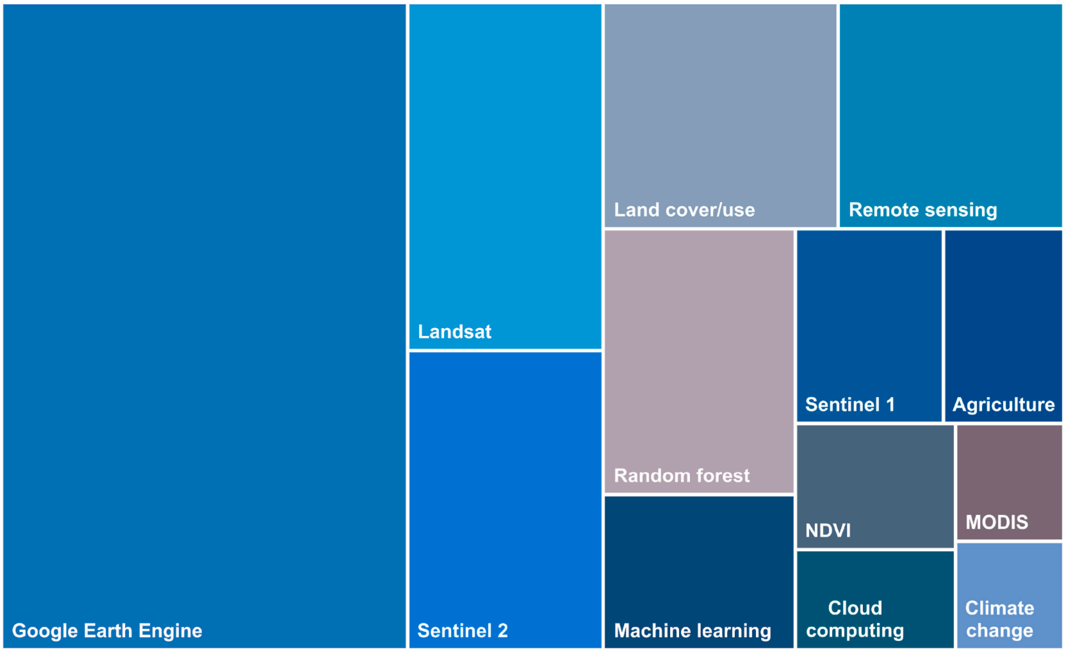


Fig. 3. Keyword frequency from articles on GEE. Rectangle size displays the frequency rate of the cited keyword.

addition to general terms, such as 'Google Earth Engine' or 'Remote Sensing', the most used keywords are relevant to the satellite platforms, Landsat, Sentinel 2, Sentinel 1 and MODIS being from the highest to the lowest recurrence. An important share of the keyword references was related to processing algorithms. Random forest' was the most frequent, followed by 'Machine Learning', 'NDVI' as well as the term 'Cloud computing'. Another set of frequently-used terms in research applications includes 'Land cover/use', followed by 'Agriculture' and 'Climate change' (Fig. 3). 'Water', 'Urban', 'Forest', 'Coastal', 'Time series' or 'SAR' were other, but less frequent words.

3.3. *Satellite features*

The imagery provided by satellite platforms included in the GEE cloud computing system comes mainly from Landsat, Sentinel, MODIS and ASTER missions (Amani et al., 2020a). Research studies often use images from several satellite sensors with similar properties, thus increasing the number of used satellites compared to the reviewed articles. The results until 2019 showed that the Landsat mission imagery was the most widely used for studies on GEE, with Landsat 8 being the most frequently adopted satellite (Tamiminia et al., 2020). This trend has continued to present, with Landsat 8 images from the OLI and TIRS sensors being even more commonly applied (Fig. 4). A noteworthy data was the significant growth use of Sentinel 1 and Sentinel 2 satellites, as these satellites increased the most in terms of percentage of use in the studies on GEE.

The European Commission via European Space Agency (ESA) has provided the Sentinel Earth Observation missions of the Copernicus programme. The products supplied are mainly data collected from Sentinel 1 dual polarimetry SAR and Sentinel 2 multispectral optical Earth observations. Such sensors enhance the spatial, spectral and temporal resolution of all other open satellites, providing a valuable tool for the analysis of spatial research. According to research goals, Sentinel and Sentinel 2 imagery were used independently, but, in some cases, both satellites were applied in combination. Some examples can be found in wetland inventories (Mahdianpari et al., 2020a), identification of flooding in crops (Singha et al., 2020), or land cover classifications (Stromann et al., 2020).

Despite the limitations of GEE in radar data processing (Amani et al., 2020a), SAR-based work has increased considerably, as it can be more clearly observed in the analysis of sensor-type data (Fig. 5). No records of published articles using studies on SAR are available until 2017, but from this start point an upward trend begins (Tamiminia et al., 2020). Within the reference period, the use of different types of sensors has become more diversified, whereas optical sensors are no longer the most widely used. In this sense, SAR data, exclusively used or combined with optical spectral data, have become the preferred datasets to be implemented.

The application of ready-to-use data is worthy to mention. Such information is a set of pre-processed data available to GEE platform users, which is mainly structured into climatic, topographic and environmental datasets, such as temperature, precipitation, humidity as well as different spectral indices (mainly regarding vegetation) from satellite imagery (Kumar and Mutanga, 2018). Due to its easy accessibility and broad range of data, it has been increasingly used in articles on GEE in the last years, and applied in a wide

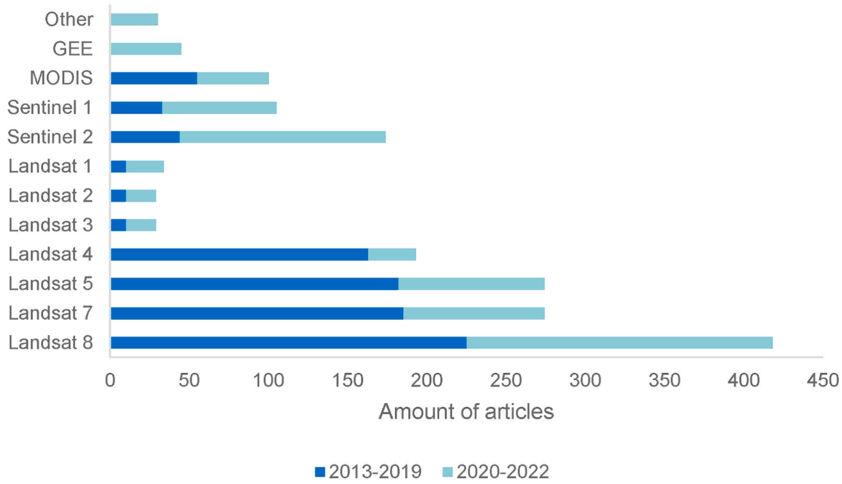
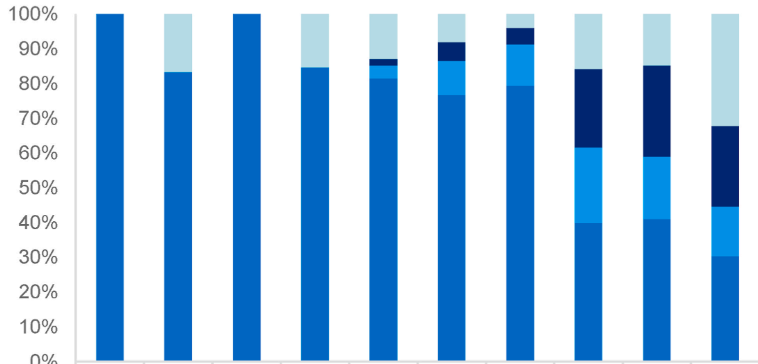


Fig. 4. Satellites used in articles on GEE. 'Other' stands for images from other satellites incorporated in the analyses by authors. GEE: GEE data catalog at user's access. Values from 2013 to 2019 extracted from Tamiminia et al. (2020).



	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Ready to use	0	1	0	6	7	9	5	21	23	18
SAR	0	0	0	0	1	6	6	30	41	13
Optic/SAR	0	0	0	0	2	11	15	29	28	8
Optic	2	5	10	33	44	86	100	53	64	17

Fig. 5. Sensor type used in articles on GEE per year. Values from 2013 to 2019 extracted from Tamiminia et al. (2020). Values from 2022 extracted until 1 May.

scope of previously less usual RS application studies, such as spatial distribution of vector-borne diseases (Li et al., 2022), animal species distribution modelling (Crego et al., 2022) or archaeology (Lasaponara et al., 2022).

3.4. Processing methods

Besides a huge data catalogue, one of GEE's strengths is the system's architecture design. The GEE architecture is based on a collection of technologies in Google's data hub environment, including cluster management systems, distributed databases, Google file systems, a framework for running parallel pipelines as well as a web-based database supporting geometric data tables containing attributes (Gorelick et al., 2017). Such a design provides to users the ability to query from the GEE library, which nearly has a thousand functions, ranging in operationality from simple algebraic functions to powerful geostatistical, image processing and machine learning functions.

Machine learning, which takes part of artificial intelligence processes, focuses on the development of algorithms to train models aimed at making decisions or predictions (Maxwell et al., 2018). Machine learning methods have been successfully used for processing remotely sensed data, being a core part of the GEE platform's computational algorithms. However, at present the lack of resources such as hyperparameter adjustment in GEE is a major limitation. Google's inclusion of process-oriented computational tuning tools would minimise offline workflows (Zhou et al., 2020).

In our analysis, 1049 processing operations have been identified, which were classified according to the source of the implemented satellite imagery (Table 3). The commonly used algorithms in the reviewed articles include non-parametric classification methods, among which the most frequent were Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Trees (CART), Decision Tree (DT), and Artificial Neural Networks (ANN). Non-parametric models have become widely used by researchers, since these models allow more adaptability and can process a large amount of data with no prior knowledge. In addition, non-parametric algorithms are assumption-free models, and therefore they are better suited to the inherent characteristics of remotely sensed datasets, which may not be normally distributed (Holloway and Mengersen, 2018).

In our review, RF was the most often reported classification method in the GEE platform with 326 utilizations (Table 3). Several reasons explain this higher frequence, the major factors being the robustness of the algorithm as well as the lower susceptibility to the training data quality, as opposed to other non-parametric classifiers (Zhou et al., 2020; Shamshiri et al., 2022). Data collected from Landsat 8 (84 records) and Sentinel 2 (67) were the most frequently satellite imageries used to implement RF classification techniques. An analysis of the distribution of processing methods associated with the satellite platforms (Fig. 6) showed that RF had the highest interquartile range (IQR), although a low median in relation to the whole dataset, indicating applications of RF on all satellite platforms analysed, but mainly concentrated on Landsat 8 and Sentinel 2.

SVM was at the second rank among the algorithms with a total of 94 cases, followed by CART with 67 cases (Table 3). Nevertheless, CART shows a higher IQR, due to more balanced use across all the satellite platforms compared to the SVM algorithm (Fig. 6), which targets Landsat 8 and Sentinel 2 satellites. This is presumably due to the greater efficiency and simplicity of CART algorithm (Hu et al., 2017; Ji et al., 2021), as opposed to the greater complexity of the SVM algorithm, which is more sensitive to the selection of the characteristics for training areas (Stromann et al., 2020) as well as to the adjustment of parameters, such as the function and kernel size (Holloway and Mengersen, 2018). Finally, the DT and ANN were the less used algorithms, with 20 and 12 cases, respectively (Table 3). DT algorithm is based on hierarchical associations and offers an easy-to-interpret set of rules, does not require extensive design and training, and it is computationally efficient (Maxwell et al., 2018); however, it has been used very rarely in the reviewed articles (Yuanqiang et al., 2020). ANN is a data-driven, self-adaptive technique that has been successfully used in the analysis of RS data. However, its limited application on the GEE platform is probably due to the fact that ANN algorithms are not supported in GEE's built-in functions and it lacks high computational rates (Amani et al., 2020b), time-consuming training, difficulties to choose the type of network architecture as well as difficulties with local minimum training (Tamiminia et al., 2020).

In addition to these classification methods, other algorithms have been found in the reviewed paper. Due to their reduced number, these algorithms were grouped into a set named 'Other Classification Methods' (OCM). Within this group, parametric classifiers, such

Table 3
Number of processing methods categorised by satellite imagery used in the articles on GEE.

Method	L8	L7	L5	L4	L3	L2	L1	S2	S1	MODIS	GEE	Other	TOTAL
ANN	1	0	0	0	0	0	0	5	2	2	2	0	**12**
SVM	20	7	7	5	4	4	4	24	8	4	4	3	**94**
DT	4	1	2	1	1	1	1	4	3	0	1	1	**20**
CART	20	8	11	3	3	3	4	12	2	0	1	0	**67**
RF	84	38	34	10	8	8	12	67	30	12	13	10	**326**
OCM*	9	4	3	1	0	0	0	2	1	0	2	0	**22**
SA*	5	2	2	0	0	0	0	9	3	1	1	0	**23**
RM*	10	5	5	0	0	0	0	6	0	0	1	3	**30**
GEEapp*	37	23	22	11	6	6	8	19	9	8	10	6	**165**
Spect. Analysis*	67	29	35	13	9	9	10	37	27	27	22	5	**290**
TOTAL	**257**	**117**	**121**	**44**	**31**	**31**	**39**	**185**	**85**	**54**	**57**	**28**	**1049**

Note: *A group of methods containing different algorithms. Several methods and satellites could be used in a single article. Methods: Artificial Neural Networks (ANN); Support Vector Machine (SVM); Decision Tree (DT); Classification and Regression Trees (CART); Random Forest (RF); Other Classification Methods (OCM); Segmentation Algorithms (SA); Regression models (RM); GEEapp: Algorithms implemented within GEE; Spect. Analysis: Spectral Analysis used by acquisition of surface reflectance from spectral data. Satellite names: Landsat (L); Sentinel (S).

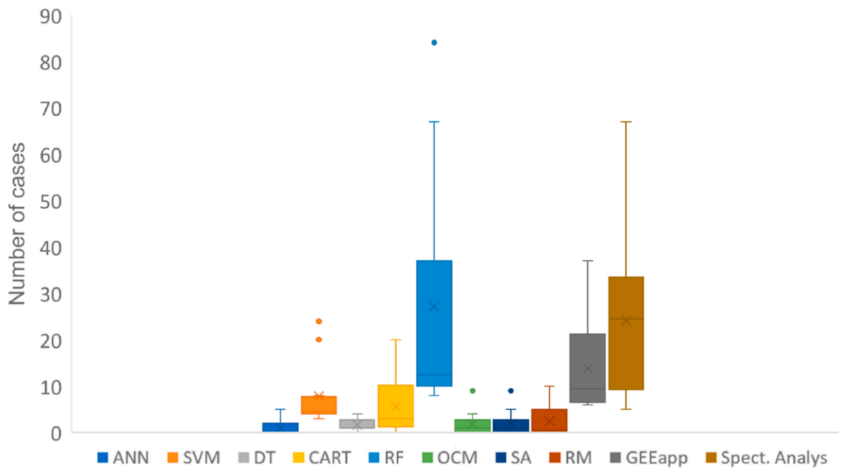


Fig. 6. Distribution of processing methods by satellite platform set used in the articles on GEE. Several methods and satellites could be used in a single article. Methods: Artificial Neural Networks (ANN); Support Vector Machine (SVM); Decision Tree (DT); Classification and Regression Trees (CART); Random Forest (RF); Other Classification Methods (OCM); Segmentation Algorithms (SA); Regression models (RM); GEEapp: Algorithms implemented within GEE; Spect. Analysis: Spectral Analysis used by acquisition of surface reflectance from spectral data.

as Gaussian Mixture Model (GMM) (Pourghasemi et al., 2021), Minimum Distance (MD) (Mahdianpari et al., 2020b), and other clustering methods including K-Means (KM) (Gulácsi and Kovács, 2020), Continuous Change Detection and Classification (CCDC) (Arévalo et al., 2020), or Automatic Generation of Training samples and One-class machine learning Classification (AGTOC) (Yang et al., 2021) can be found.

Moreover, we found clustering methods, which have been grouped into the category 'Segmentation Algorithms' (SA). These methods are image segmentation algorithms as techniques commonly used in digital image processing and analysis to divide an image into multiple parts or regions, usually based on the pixel features of the image. The most frequent clustering method found in the review was the OTSU algorithm (Otsu, 1979), a variance-based technique to find the threshold value of the smaller weighted variance between foreground and background pixels. Due the robustness and performance advantages when compared to others, this algorithm has been extensively tested in the application of Sentinel 1 data (Jiang, Z. et al., 2021). Other examples of segmentation methods are related to Detecting Breakpoints and Estimating Segments in Trend (DBEST) (Xulu et al., 2021) or Connected Component Segmentation (CCS) (Xia et al., 2020) techniques.

A separate mention should be made to the regression methods. The cases found in this review were grouped in the category 'Regression models' (RM), including algorithms such as Multiple Linear Regression (MLR), Geographically Weighted Regression (GWR), and Geographically Weighted Logarithmic Regression (GWLR) (Jiang, F. et al., 2021), or Gaussian Process Regression (GPR), as a nonparametric bayesian approach to regression (Pipia et al., 2021). As a linear method, geographically weighted regression (GWR) explores spatial changes of research objects and related factors, applied in many cases to predict future outcomes in land transformation (Jiang, F. et al., 2021). GWLR combined with GWR offers variation in the local estimation of spatially classified categories. In some studies, the performance of GWLR was analysed with the conventional Ordinary Least Square Regression (OLSR) technique applied to satellite imagery, showing a better accuracy estimation by GWLR compared to OLSR (Mishra et al., 2021).

Finally, there are two sets of algorithms that serve as a catch-all for a large number of methods identified in this review. 'GEEapp' includes all the algorithms implemented within GEE using the JavaScript or Python APIs. A summary of these methods can be Surface Energy Balance Algorithm for Land (SEBAL) (Laipelt et al., 2021), Bayesian Estimator of Abrupt change, Seasonality, and Trend (BEAST) (Hu et al., 2021), or Analytical hierarchy process (AHP) (Bhattacharya et al., 2022). Meanwhile, 'Spectral Analysis' refers to acquisition of surface reflectance from spectral data. Examples among them are the analysis of spectral indices and pixel-phenology-based algorithms to map croplands using satellite imagery (Di et al., 2021) or a global automatic Burned-Area (BA) algorithm based on the temporal evolution of burning probabilities (Roteta et al., 2021). Such a range of algorithms explains the large use of both classes of methods, and hence the application of these methods across all types of satellite datasets, as shown in Fig. 6.

3.5. Applications

The range of spatial analysis provided by GEE is quite extensive, thus providing a wide and varied dataset that allows the development of a large set of research applications. This review found a high diversity of applications, which were categorised into eight classes, and in a further class labeled 'Other', as a compilation of less frequently-used applications (Table 4). As examples, this category includes: (i) a study of Heron Reef in the southern Great Barrier Reef (Australia), based on a classification of coral, sand and rock/dead coral substrates by analysis of semi-automatic workflow for drone image processing using GEE platform (Bennett et al., 2020); (ii) the detection and monitoring of sand deposition on photovoltaic solar panels in arid regions, using multitemporal remote sensing data (Supe et al., 2020); and (iii) the enhancement of animal movement analyses (Crego et al., 2021) and implementation of species distribution models (Crego et al., 2022). Studies on public health have also been of interest, such as mapping of malaria vector

Table 4
Number of applications categorised by satellite imagery in articles on GEE.

Application	L8	L7	L5	L4	L3	L2	L1	S2	S1	MODIS	GEE	Other	TOTAL
Agriculture	18	12	9	2	2	2	3	32	12	6	6	0	**104**
Climate change	9	4	2	1	1	1	1	4	2	3	5	0	**33**
Natural hazards	20	10	12	4	4	4	4	14	12	10	11	2	**107**
Forestry	18	8	9	3	1	1	3	19	7	6	5	2	**82**
Water resources	44	21	24	10	5	5	6	24	19	6	5	2	**171**
Soils	22	8	7	2	1	1	1	7	3	9	3	2	**66**
Urban	9	2	4	1	1	1	2	4	0	0	2	0	**26**
Land use	33	15	17	3	3	3	3	16	9	1	4	2	**109**
Other	20	9	9	4	1	1	1	10	8	6	6	2	**77**
TOTAL	**193**	**89**	**93**	**30**	**19**	**19**	**24**	**130**	**72**	**47**	**47**	**12**	**775**

Note: Several applications and satellites could be used in a single article. Satellite names: Landsat (L); Sentinel (S).

suitability (Frake et al., 2020) or studies based on spatio-temporal analysis of air pollutants before and during the first wave COVID-19 outbreak (Ghasempour et al., 2021).

In more detail, water resources (WR) applications were the most frequent (Table 4), and were applied to all sensors available on the GEE platform, as shown by the IQR in the box plot (Fig. 7). Images from Landsat 8 sensors, alongside Landsat 7 and Sentinel 2, were the most frequently-used imagery. A broad variety of applications in this category was observed, with coastal research and detection in surface water areas being the most common. Regarding the first case, the studies are related to the detection of coastal changes (Chen, D. et al., 2022) and the analysis of ocean dynamics (Xu and Liu, 2022) from long time series mapping. Numerous studies have also been carried out in wetlands, aiming at monitoring of changes on a large scale. The most common sensors for these analyses were those from the Landsat series (Wang, R. et al., 2020; Dervisoglu, 2021), although active satellite sensors, such as C-band synthetic aperture radar of Sentinel 1, were also applied (Gulácsi and Kovács, 2020). Lake surfaces have also been studied, as, for instance, in research about the hydrological asynchrony of Chad Lake (Li et al., 2021) or in an application to retrieve long-term surface temperature of San Pedro Lake in Chile (Pedreros-Guarda et al., 2021). Articles based on water resources and water quality are less frequently reported (Kumari et al., 2021; Wang, L. et al., 2020), and the same was noticed for groundwater studies (Afraz et al., 2021; Han et al., 2022).

The land use/coverage (LU) and natural hazards (NH) applications are at the second and third rank after WR in researches using the GEE platform, providing a trend similar within the period 2013-2019 (Tamiminia et al., 2020). Most of the articles related to LU applications developed change detection systems and spatial-temporal dynamics (Lu et al., 2021; Luo et al., 2021). For instance, Chen, D. et al. (2022) applied detection of changes in coastal zone combined with a method for the long time-series mapping, and in land use based on multi-source data fusion. Other methods use continuous change detection and classification (CCDC) algorithms, which analyses all available image data to model temporal-spectral characteristics, including seasonality, trends and spectral variability (Arévalo et al., 2020; Chen et al., 2021). The NH studies mainly focus on three specific research areas, such as wildfires (Piao et al., 2022; Singh et al., 2022), floods (Tiwari et al., 2020; Mehmood et al., 2021) and droughts (Khan and Gilani, 2021; Mehravar et al., 2021). Nevertheless, other studies have been found about the use of GEE to rapidly monitor impacts of geohazards on ecological quality in highly-susceptible areas (Yan et al., 2021), the monitoring of glacial lake outburst flood susceptibility using Sentinel 1 SAR data

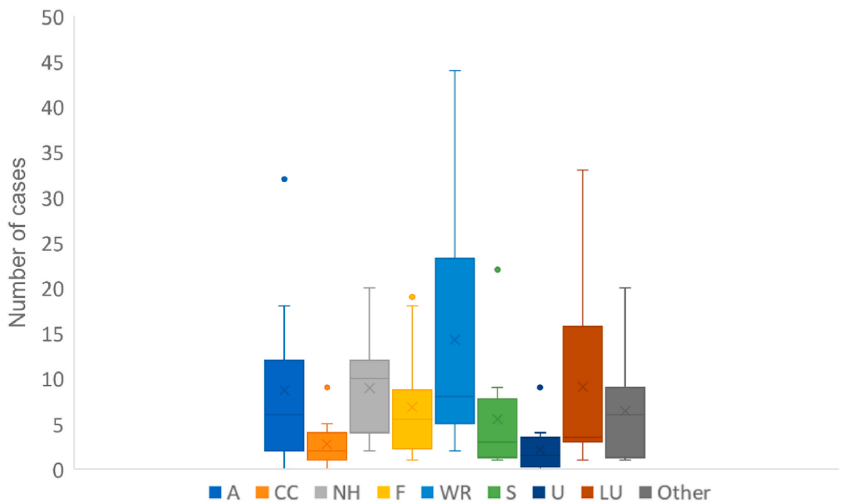


Fig. 7. Distribution of applications by satellite platform set. Several applications and satellites could be used in a single article. Applications: Agriculture (A); Climate change (CC); Natural hazards (NH); Forestry (F); Water resources (WR); Soils (S); Urban (U); Land use (LU).

and persistent scatterer interferometry (Wangchuk et al., 2022), and the monitoring of volcanic thermal anomalies on a global scale (Genzano et al., 2020). This large variability of studies on NH is noted at the highest median across all applications, although not showing the largest IQR (Fig. 7). This indicates a large use of all the sensor and imaging possibilities offered by GEE.

Applications in agriculture (A) are also an important set of items to use in GEE as well as the broad utilization of satellite resources. This category clearly shows a wider use of Sentinel 2 imagery as outlier (Fig. 7), indicating a requirement for higher spectral and spatial accuracy compared to Landsat Series (Table 4). A growing topic under investigation is the mapping and monitoring of irrigated crops in arid environments (Yao et al., 2022; Han et al., 2022), including the effect of increasing irrigated area in the environment (Naboureh et al., 2021). An additional topic is related to crop detection, using several methods, such as RF machine learning algorithm embedded in GEE to retrieve pixels screening, training samples generation, analyses of Leaf Area Index and fraction of photosynthetically active radiation (Sun et al., 2022), ANN algorithm and Sentinel 1, Sentinel 2 images to produce an object-based ACI map (Amani et al., 2020b), or cropland mapping based on phenological metrics, environmental covariates, and machine learning (Htitiou et al., 2021; Cao et al., 2021).

Articles included in the 'forestry' category (F) did not show a clear pattern of applications, in spite of the varied utilization of satellite imagery sources (Table 4). The review found a wide variety of approaches, covering issues such as classification of Mediterranean forest habitats on seasonal Sentinel 2 time-series and input image composition optimisation (Praticò et al., 2021), monitoring of temperate forest degradation using Landsat imagery (Chen et al., 2021), identification and monitoring of threats to key biodiversity areas in Africa using MODIS and NOAA imagery (Beresford et al., 2020), and mapping of mangrove canopy phenology (Valderrama-Landeros et al., 2020; Cissell et al., 2021). In contrast, studies reported under the category 'soil' (S) presented clearly defined fields of research, which were grouped into the mapping of soil physico-chemical properties (Xiao et al., 2020; Greifeneder et al., 2021; Ye et al., 2021; Aksoy et al., 2022; Luo et al., 2022) and studies on soil erosion processes (Wang and Zhao, 2020; Alexakis et al., 2021).

On the other hand, articles included in the categories 'climate change' (CH) and 'urban' (U) were the least frequent in GEE. A broad range of studies were found in the CH category, the most representative being the analyses of impacts of droughts and floods (Venkatappa et al., 2021) or glacier area and snow cover changes and snowmelt detection (Liang et al., 2021; Zhang, J. et al., 2021). The studies included in U category are mainly oriented towards the detection of urban areas changes and growth (Zhang, Z. et al., 2021; Xue et al., 2021). Both categories have similar IQR ranges (Fig. 7), although CC shows a slightly higher median value. This is presumably due to the higher implementation of algorithms in GEE as well as the use of the MODIS sensor (Table 4), which was not used in category U, likely as the spatial resolution required was not achieved.

3.6. COVID-19 studies

Within the reviewed articles, seven studies were found about computations in GEE related to the effects of COVID-19 pandemic. The reference period of this paper overlaps the duration of COVID-19 pandemic, and thus it is worth to mention research using the GEE platform on applications related to COVID-19 effects. Therefore, articles containing the terms 'Google Earth Engine' AND 'COVID' in the title, keywords or abstract were further identified. This operation resulted in a collection of 23 articles, including two articles published in 2020, 13 in 2021, and eight in 2022, which were screened for further evaluation. Three articles were excluded, since the authors did not really used GEE as analysis tool, and four additional articles did not report results that were relevant to COVID-19, such as the significance of effects of COVID-19 on human health, socio-economics or environment.

The main application of the screened articles was related to the monitoring and quantification of global changes in atmospheric pollutants due to COVID-19, accounting for more than 75% of the articles (Sannigrahi et al., 2021; Moazeni et al., 2022). Other applications were mainly about the effect on agricultural productivity (Htitiou et al., 2021) or the observation of maritime traffic interruption during the COVID-19 lockdown (Rodríguez-Benito et al., 2021). As far as we suppose, many studies are still under development or still collecting field data (Clemente-Suárez et al., 2021). Thus, it is possible to expect that the number of these articles will increase in coming months.

3.7. Geographical distribution

An important issue of this review was the spatial distribution of the studied territories. For this purpose, the study areas in the articles on GEE have been counted, in order to identify the countries included in this geographical analysis. Articles focusing on global and continental areas were excluded, since these had not specific case studies. In the case of articles analysing specific areas (on the local scale), the study areas were reported by mapping at the country scale. Furthermore, for articles with several study areas in different countries, the latter were counted as separate country case studies. It is important to highlight that neither statistical relationships nor trends between the used methods or applications with different geographical elements have been found in this meta-analysis; therefore, this section will only describe the results from a spatial perspective.

In general, research was reported in 86 countries, of which China was the country accounting for most studies (118), followed far behind by United States (33), India (27), Iran (19), Brazil (16), Australia (10) and Italy (10) (Fig. 8). The increase in the number of articles from China is noteworthy, but also proportionally increasing papers from Iran and Italy have been recorded against 50, 1 and 0 articles, respectively, between 2013 and 2019 (Tamiminia et al., 2020). In contrast, it is particularly noticeable the decreasing trend in the number of publications from United States and Canada, from 77 to 33 and 17 to 6 publications, respectively, in the two reference periods (2013-2019 and 2020-2022).

By an approach on a larger scale, when values were aggregated on a continental level, a decrease in studies was observed in all continents except Asia. In the latter continent, the articles increased from 164 to 240, almost doubling the percentage of studies between 2013-2019 and 2020-2022 (34% and 61%, respectively) (Fig. 9). In spite of this decrease in the total number of articles observed in almost all continents, the percentage of published articles on the total number has practically remained constant in South

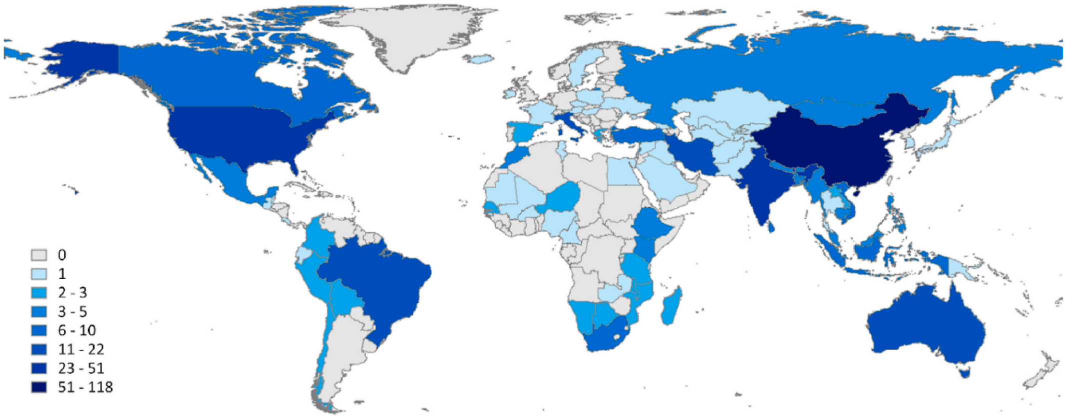


Fig. 8. Geographical distribution of the number of articles on GEE in the different countries. Grouping by category has been done in ArcGIS v.10.5 applying the geometric interval classification method.

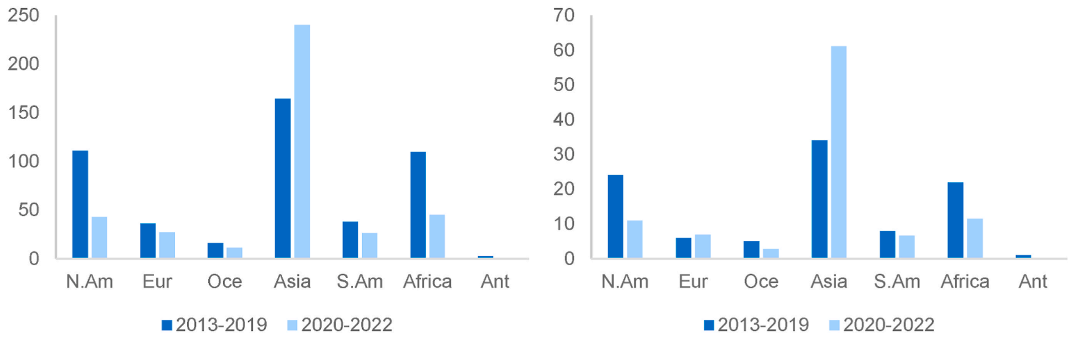


Fig. 9. Number (left) and percentage on the total number (right) of published articles according to the geographical study area at the continental level. Abbreviations horizontal axis: N.Am (North America), Eur (Europe), Oce (Oceania), S.Am (South America), Ant (Antarctica). Values from 2013 to 2019 extracted from Tamiminia et al. (2020). Values from 2022 extracted until 1 May.

America, while, in Europe, it has slightly increased from 6% (2013-2019) to 7% (2020-2022). Only one article has been recorded in this review in Antarctica, an ecologically significant territory, which is highly vulnerable to climate change effects. This article is related to the detection of ice melt using Sentinel 1 SAR imagery (Liang et al., 2021).

One of the major advantages offered by the GEE platform is its high capacity of temporal and spatial computation, but only 8% (Global and Continental areas) of the reviewed articles are relevant to large geographical zones (Table 5). The lack or difficulty to obtain ground control data to calibrate models and algorithms on a large geographic extent leads to a scarce development of large-scale studies (Bian et al., 2020).

The global-scale studies are mainly based on the application of algorithms implementing spectral indices for detection and monitoring of environmental factors. Estimates of global drought (Khan and Gilani 2021), land surface temperature (Ermida et al., 2020), surface soil moisture (Greifeneder et al., 2021) or land surface phenology (Descals et al., 2021) were found among the main studies in this category. Other research was oriented towards the development of methodologies for implementation and improvement of topographic data from Digital Elevation Models (Safanelli et al., 2020; Capolupo, 2021). Studies were also found based on the detection of land cover changes over urban areas, generating global impervious surface mapping by combined optical images from Landsat 8, SAR images from Sentinel 1 and NTL images from the Visible Infrared Imaging Radiometer Suite (VIIRS) available on the GEE platform (Zhang et al., 2020; Kuang et al., 2021).

Articles about the continental dimensions were quite rare, although studies carried out in some large countries, such as Canada or China, could be added under this category, as the geographical extend of these studies are more closely related in working protocols

Table 5
Number and percentage of articles on GEE related to study scale.

Study scale	Articles	%
Global	15	4.4
Continental	11	3.2
Country	36	10.5
Local	281	81.9
TOTAL	**343**	**100**

and interpretation of findings (Mahdianpari et al., 2020c; Wei et al., 2022). In line to the trend of all other reviewed publications, studies focusing on Asia were the most frequent and with varying topics. Agronomic studies related to new approaches to mapping rice fields in monsoon-dominated areas (Maiti et al., 2022) or the development of methods to improve the accuracy of cropland data are some examples (Li and Xu 2020). The effects of natural hazards, such as the impact of droughts and floods on cropland and agricultural production, have also been assessed (Venkatappa et al., 2021) together with the development of quantitative mapping of wind erosion potential of soil (Wang, W. et al., 2020). Other examples in Europe were the assessment of the C-factor in the USLE (Universal Soil Loss Equation) method estimating soil erosion (Alexakis et al., 2021), the quantification of fundamental vegetation traits (Reyes-Muñoz et al., 2022), the monitoring of threats to Key Biodiversity Areas in Africa (Beresford et al., 2020), or the development of an algorithm for river discharge retrieval in North America (Riggs et al., 2022).

The smaller-scale (country and local) research was over 90%, and China, USA and India represent over half the cases (Table 5). A comparative analysis between these countries could provide an interesting insight regarding GEE use and applicability at a detailed scale. About the implemented methods, all classes were used in China, RF, automated algorithms within GEE and analysis of surface reflectance from spectral data being the most commonly used algorithms (Fig. 10). Likewise, both the RF and surface reflectance analysis methods (SpectAnalysis) were most commonly used in India, while, in the United States, the 'SpectAnalysis' and Support Vector Machine methods were mainly.

On a geographical basis, the applications implemented in each territory seems to be more important than methods, since this focus allows to understand the relevant issues in different regions. Agriculture was the most applied topic in China. Due to rapid population growth, expansion of residential areas and increasing agricultural demand for non-food uses (biofuels), a significant increase in food production and crop surface area has been observed in this country (Guo et al., 2022). Territorial transformation and land use change are thus a main issue in China, and this is also evidenced by the large number of publications included in the LU category, and, in particular, focusing on the sprawl of urban areas (Zhang and Zhang, 2020). Water resources were another major issue, not only in China, but also in USA and India, leading to the largest number of publications in the WR class. The NH class showed similar values in all the analysed countries, indicating a prominence effect of natural hazards in the three large territories. Flooding is a common issue in all three cases (Yang et al., 2020; DeVries et al., 2020; Lal et al., 2020), while studies of the effects of monsoon on agriculture in India (Maiti et al., 2022) or of the effects of drought on agriculture in China (Zhao et al., 2021) were also commonly found.

3.8. *Citation impact metrics*

In order to assess the contribution of articles on GEE in the international scientific community, a series of citation metric analyses from reviewed articles have been conducted. Citation counts in journals show a clear leading of 'Remote Sensing' (RS), followed by far behind by 'Remote Sensing of Environment' (RSE), 'ISPRS Journal of Photogrammetry and Remote Sensing' (JPRS), and 'IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing' (JSTAEORS) (Fig. 11). However, an adjustment factor, calculated as the ratio of citation count to number of published articles, provides a more realistic comparison. In this case, RSE is the most cited journal, reporting a ratio of 30.4 citations per article, which is a remarkable value considering that most articles have been published from a year or even less. Another interesting case is the Canadian Journal of Remote Sensing (CJRS), which shows a ratio of 27 citations of two publications.

Concerning publishers, a similar pattern as for the analysis of journals was observed. In more detail, MDPI obtained 41% of the total citations for 151 publications, of which 108 were relevant to RS (Fig. 11). Such a high publishing activity of MDPI has opened a controversial debate in the scientific editorial system with the appearance of so-called "predatory" journals based on the gold open access model, where certain journals prioritises quantity over quality (Beall, 2021; Oviedo-García, 2021). Several authors suggest implementing a reward-based review of academic publishing, supported by a set of trusted criteria-based guidance system, rather than

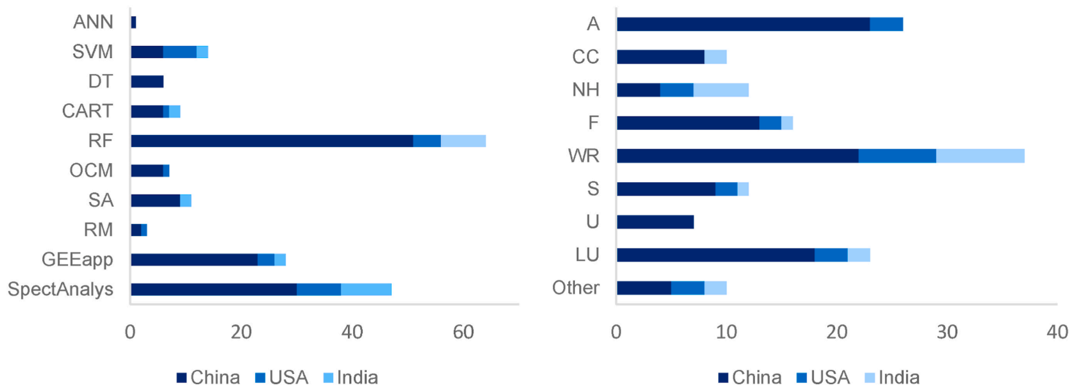


Fig. 10. Number of methods (left) and applications (right) in articles on GEE from the main representative countries. Keys: Methods: Artificial Neural Networks (ANN); Support Vector Machine (SVM); Decision Tree (DT); Classification and Regression Trees (CART); Random Forest (RF); Other Classification Methods (OCM); Segmentation Algorithms (SA); Regression models (RM); Algorithms implemented within GEE (GEEapp); Spectral Analysis used by acquisition of surface reflectance from spectral data (SpectAnalysis). Applications: Agriculture (A); Climate change (CC); Natural hazards (NH); Forestry (F); Water resources (WR); Soils (S); Urban (U); Land use (LU).

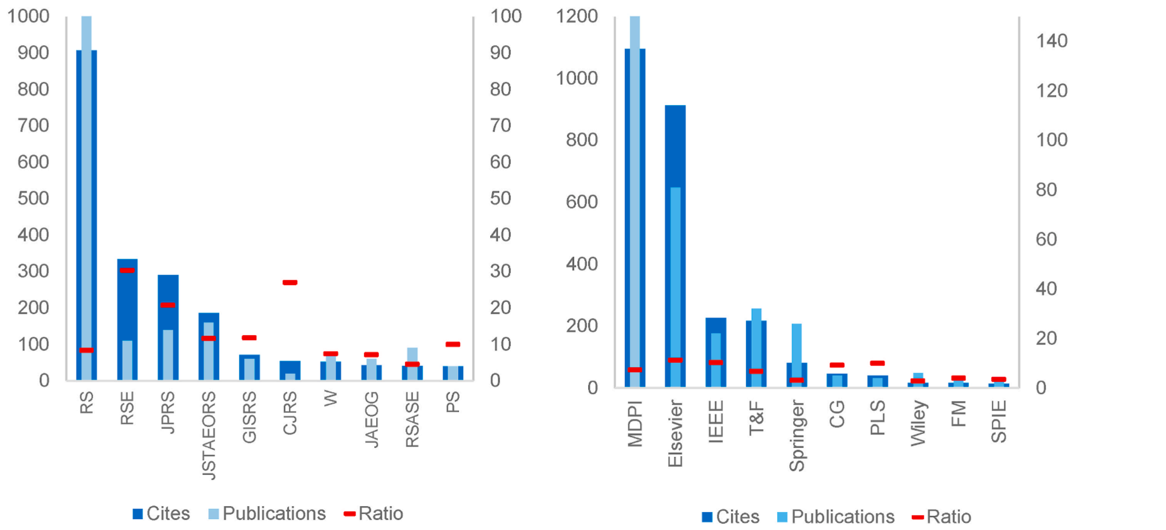


Fig. 11. Analysis of citation impact metrics for journals and publisher of articles on GEE. Notes: Total number of citations is in dark blue bar and numbered on the left axis; total number of publications is in light blue bar and numbered on the right axis); ratio cites to publications is labeled with red marks and numbered on the right axis. Journal Acronyms: Remote Sensing (RS); Remote Sensing of Environment (RSE); ISPRS Journal of Photogrammetry and Remote Sensing (JPRS); IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (JSTAEORS); GIScience and Remote Sensing (GISRS); Canadian Journal of Remote Sensing (CJRS); Water (W); International Journal of Applied Earth Observation and Geoinformation (JAEOG); Remote Sensing Applications: Society and Environment (RSASE); PloS one (PS). Right graph: Publishers metrics. Publishers Acronyms: Multidisciplinary Digital Publishing Institute (MDPI); IEEE-Inst Electrical Electronics Engineers Inc (IEEE); Taylor & Francis (T&F); Copernicus Gesellschaft (CG); Public Library Science (PLS); Frontiers Media (FM); SPIE-Soc Photo-Optical Instrumentation Engineers (SPIE). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

proposing blocklisting systems, which often have insufficient specific and overly broad criteria and a certain subjectivity (Dony et al., 2020; Teixeira da Silva et al., 2022).

About citation metrics related to methods and applications, a citation ratio (cites by publication) was also applied, but, in this case, this task was more complex, due to the fact that the same article may use several methods and applications, as explained in sections 3.4 and 3.5. About the method citation metrics, the 'RF' and the set of algorithms contained in 'Spect. Analysis' were the most cited methods. However, the citation ratios show a higher impact on the 'DT' analysis methods, 'GEEapp' and SA computing techniques (Fig. 12). Regarding application citation metrics, excluding the 'CC' cases, the remaining applications showed a high number of citations, with agriculture-related applications being the mostly cited. Similar results can be observed in most citation ratios, the 'U' applications standing out above all, due a 3-fold ratio. The highest ratio shown by urban studies is due to the relative low number

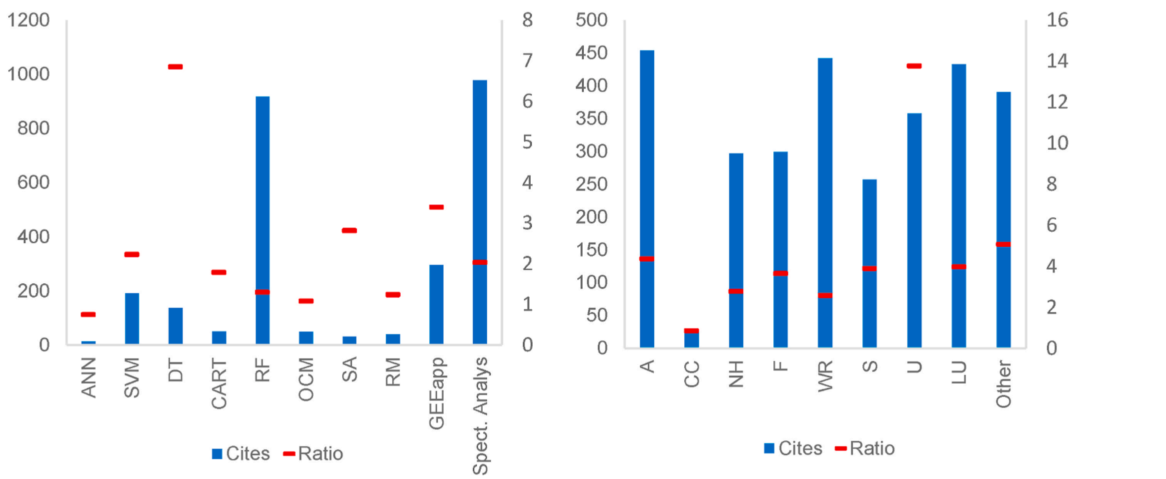


Fig. 12. Analysis of citation impact metrics for methods (left) and applications (right) in articles on GEE. Red marks refer to the ratio cites/methods or applications used, numbered on the right axis. Method acronyms: Artificial Neural Networks (ANN); Support Vector Machine (SVM); Decision Tree (DT); Classification and Regression Trees (CART); Random Forest (RF); Other Classification Methods (OCM); Segmentation Algorithms (SA); Regression models (RM); GEEapp: Algorithm acronyms: Spect. Analysis: Spectral Analysis used by acquisition of surface reflectance from spectral data. Right graph: Applications metrics. Agriculture (A); Climate change (CC); Natural hazards (NH); Forestry (F); Water resources (WR); Soils (S); Urban (U); Land use (LU). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

of relevant articles, with two papers having a very high number of citations (Wang, Y. et al., 2020; Liu et al., 2020). Nonetheless, this indicates an increasing interest in urban issues research.

3.9. Challenges for remote sensing big data computing in the future

Among the most important challenges faced by RS is related to managing, processing and interpreting Big Data. Advances based on high-performance computing (HPC) have made it possible to address the massive computational demands generated by the data provided by RS (Wang et al., 2018; Sabri and Aouad, 2021). As a result, nowadays, data computational capacity is no longer the bounding factor (Cavallaro et al., 2022), instead the emphasis is focused on data availability. In addition, parallel programming for RS applications in cluster systems are considered as difficult and error-prone computational processes (Ma et al., 2015).

RS data increasingly provide higher dimensionality, higher spatial resolution and higher temporal resolution, causing a significant increase in volume, variety, as well as decreases in data velocity and veracity (Sabri and Aouad, 2021). To process these complex datasets, robust computational services combined on cloud-based data analytics platforms have developed. Systems such as 'Apache Hadoop' or 'Plenar.IO' offer opensource solutions, showing high versatility. 'Planet Analytics', Microsoft's 'Azure AI platform', 'Cloudera' and 'IBM cloud computing' are leading the way in commercial computing services, providing solid systems for companies. Offering an intermediate business model are Amazon's 'Earth on AWS′ platforms, as well as GEE, which provide free services for educational and research purposes.

Concerning the specific platform under study, GEE has limitations which should be improved. From the point of view of system applicability, the operation of the tool provides a high level of automation in resource allocation, parallelism, data distribution and retries, but this leads to a reduced user capacity to decide on a calculation's parameterisation (Gorelick et al., 2017; Tamiminia et al., 2020). In addition, the implementation of combined input data for large-scale analysis is complex, requiring additional efforts from the user in programming processes (Shelestov et al., 2017). In computation, GEE has some limitations related to time limit (Pipia et al., 2021; Han et al., 2022), memory and storage (Tamiminia et al., 2020). Lack of processing methods (Ghaffarian et al., 2020; Greifeneder et al., 2021; Shetty et al., 2021), inflexibility in the applicability of different models (Shelestov et al., 2017; Samasse et al., 2020), as well as an improvement in the dataset provided (Phalke et al., 2020; Sulova and Jokar Arsanjani, 2020; Yang et al., 2022) have also been reported.

The improvement of these aspects, coupled with the significant potential of GEE, should provide a powerful RS analysis tool. Although it will undoubtedly need to bring a turn towards new trends in data analytics, related to the requirement for real-time information processing (Qi et al., 2018; Ghosh et al., 2021), on-demand computing, as well as in-transit processing of standard RS data products (Ma et al., 2015). Big Data RS can be enhanced by the development of the Internet of Things (IoT), leveraging the evolution of Machine Learning, supported by data virtualisation, edge computing or low-latency data transmission along with high-performance real-time processing (Sun and Scanlon, 2019; Bui et al., 2022; Zhang et al., 2022).

4. Conclusions

The 343 reviewed articles on the GEE platform are a representative literature sample, which provides the current state of the art of current research. On a bibliometric approach, 90 journals published articles on GEE in the reference period (January 2020 to April 2022), and this large number of journals reveals the multidisciplinary application of GEE platform as well as the interest of publishers towards this topic of relevance for the international scientific community. This bibliometric approach evidences that the number of articles published in the past two years and a half is very similar to the number of papers issued in the decade after the GEE platform release.

Landsat 8 imagery from the OLI and TIRS sensors are the most commonly applied in the uses provided by the satellite platforms included in the GEE cloud computing system. However, an increasing use of Sentinel 1 and Sentinel 2 was detected in percentage. The application of ready-to-use data, which is based on a set of pre-processed data available to users of the GEE platform, must be also highlighted. Due to its easy accessibility and wide range of data, it has been increasingly used by non-expert users in satellite image processing. This increased use has been also noticed for a broader scope of previously unusual RS application studies such as spatial distribution of disease transmission, modelling of animal species distribution or archaeology.

The most widespread methods for analysis processing on GEE platform are non-parametric classification methods, with Random Forest, Support Vector Machine, Classification and Regression Trees, Decision Tree, and Artificial Neural Networks in the first five ranks. Their use has become widespread among researchers, since non-parametric models allow greater adaptability and can process a large amount of data without prior knowledge of specific study areas.

A wide application spectrum of GEE, classified into eight classes, was found, 'water resources' applications being the most frequent - with application to all sensors available on the GEE platform – followed by 'Land use/land cover' and 'natural hazards' applications. 'Agriculture' was another important field of application, also in this case with a large use of the satellite resources, while the studies in the 'soil' category had clearly defined fields of research. In contrast, less applications were recorded in the 'forestry' category, in spite of the varied use of satellite imagery sources, and the applications in the categories 'climate change' and 'urban' studies were the less numerous in the reviewed articles on GEE.

It is also interesting to notice a low number of articles about COVID-19, in spite of the planetary importance of the pandemic effects. The main applications were the monitoring and quantification of global changes in air pollutants induced by COVID-19, accounting more than 75% of the articles, as well as the analysis of the effects of disease-induced lockdowns on agricultural productivity.

The reviewed articles were geographically distributed among 86 countries. China was the country accounting for most GEE studies (118), followed far behind by United States (33), India (27), Iran (19), Brazil (16), Australia (10) and Italy (10).

'Remote Sensing' and 'Remote Sensing of Environment' were the leading journals in the citation impact metrics, while the Random Forest method and the agriculture-related applications being the mostly cited.

Overall, from this review and the nested meta-analysis, it is evident that GEE provides a powerful tool for the analysis of geospatial geodata on a global scale, according to the high number of countries, in which GEE studies have been conducted. The use of massive data and time series through this open cloud-based platform offers important research opportunity framework, especially in developing countries.

Ethical statement for solid state ionics

1) This material is the authors' own original work, which has not been previously published elsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the authors' own research and analysis in a truthful and complete manner.
4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.
6) All sources used are properly disclosed (correct citation). Literally copying of text must be indicated as such by using quotation marks and giving proper reference.
7) All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.

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

The authors are unable or have chosen not to specify which data has been used.

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