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A B S T R A C T

Accurate estimation of vegetation carbon stocks is essential for monitoring climate change impacts, assessing ecosystem services, and informing global mitigation strategies. In recent years, the integration of remote sensing techniques with cloud-based platforms—particularly Google Earth Engine (GEE)—has transformed how vegetation dynamics and carbon fluxes are analyzed, largely through the widespread use of the Normalized Difference Vegetation Index (NDVI). This study presents a comprehensive bibliometric and thematic review of global research trends in vegetation carbon stock monitoring using GEE and NDVI, covering 91 peer-reviewed articles published between 2017 and early 2024. Analyses were conducted using the Bibliometrix R package and included publication patterns, leading contributors, geographic distribution, keyword evolution, sensor usage, and collaborative networks. Results indicate a substantial increase in scientific output since 2017, with China, the United States, and Brazil emerging as leading contributors. Most studies relied on MODIS, Landsat, and Sentinel-2 imagery within GEE workflows, with a growing trend toward multi-sensor integration and machine learning applications. Despite technical advancements, the review identifies persistent gaps in policy integration, in-situ validation, and geographic representation—particularly in carbon-rich but underrepresented regions of the Global South. We conclude by recommending enhanced international collaboration, expanded ground-truth validation efforts, and stronger alignment with climate policy instruments such as REDD+ and the Sustainable Development Goals (SDGs). This review provides a structured synthesis of the current state of GEE-based carbon monitoring research and highlights key opportunities to increase its scientific impact and policy relevance.

1. Introduction

Climate change remains one of the most pressing global challenges of the 21st century, demanding urgent action across multiple

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sectors. A central component of mitigation strategies lies in the monitoring and preservation of terrestrial vegetation, which acts as a natural carbon sink by absorbing atmospheric carbon dioxide (CO_2) (see Figs. 3–5).

Forests and other vegetated landscapes contribute significantly to global carbon sequestration. Accurate quantification of carbon stocks in vegetation is essential for advancing scientific understanding and supporting effective climate policy.

These measurements are not only relevant for global carbon accounting but are also vital for assessing progress toward international environmental frameworks, such as the Paris Agreement, REDD+ (Reducing Emissions from Deforestation and Forest Degradation), and the United Nations Sustainable Development Goals (SDGs)—particularly Goals 13 (Climate Action), 15 (Life on Land), and 17 (Partnerships for the Goals) (Ahmadi et al., 2023; Duchelle et al., 2018; Liu et al., 2023; Xu et al., 2016; Venkatappa et al., 2019b).

Vegetation plays a crucial role in regulating climate by absorbing CO_2, supporting soil health, maintaining water quality, and providing habitat for a wide range of species (Williams et al., 2024). Responsible vegetation management is increasingly important not only to mitigate environmental damage but also to support ecosystem recovery and adaptation over time.

Although numerous studies have used remote sensing and vegetation indices such as NDVI to assess biomass and carbon fluxes, few have examined the evolution of this scientific field itself. There is still a lack of systematic reviews that map how global research on carbon stock estimation using GEE has developed over time. Understanding these trends is essential to identify methodological patterns, thematic priorities, and existing gaps in global carbon monitoring efforts.

Remote sensing has played a transformative role in vegetation and carbon monitoring. Its ability to deliver consistent, spatially extensive, and temporally frequent observations makes it an essential tool in tracking ecosystem dynamics over time.

Among vegetation indices, the Normalized Difference Vegetation Index (NDVI) remains one of the most robust and widely applied indicators of vegetation productivity and carbon fluxes (Gamon et al., 1995; Fassnacht et al., 2019; Anderson et al., 2020; Ding et al., 2023). Derived from multispectral sensors such as Landsat, MODIS, and Sentinel-2, NDVI provides consistent, scalable observations across temporal and spatial domains (Wang et al., 2023; Bondur et al., 2024). Although alternative indices, such as EVI, SAVI, and NDWI, have been proposed, NDVI's mathematical simplicity, temporal continuity, and empirical linkage to photosynthetic activity make it highly suitable for large-scale analyses of vegetation carbon dynamics (Li et al., 2023; Gao et al., 2023). Its integration into the Google Earth Engine (GEE) framework enables rapid, standardized, and replicable estimation of vegetation carbon stocks at global and regional scales, supporting data-driven approaches to environmental monitoring and climate assessment.

This review focuses on MODIS, Landsat 8, and Sentinel-2, the most widely employed satellite platforms in GEE-based vegetation monitoring. These missions provide long-term, open-access, and harmonized surface reflectance data, ensuring consistent NDVI computation and reproducible carbon assessments. Other sensors, such as PRISMA, GEDI, or commercial constellations, offer valuable but more limited coverage and are not yet fully integrated into GEE's public datasets. Focusing on these three platforms ensures methodological consistency and global representativeness for NDVI-based carbon monitoring (Wulder et al., 2019; Chang et al., 2024; Hansen et al., 2023).

In this context, Google Earth Engine (GEE) has revolutionized environmental monitoring by providing a scalable, cloud-based geospatial processing platform. It democratizes access to petabytes of satellite imagery and robust analytical tools, integrating powerful geospatial libraries, extensive image archives, and a user-friendly scripting interface (Gorelick et al., 2017; Kumar and Mutanga, 2018; Tamiminia et al., 2020; Velastegui-Montoya et al., 2023; Ghorbanian et al., 2022). These features have substantially lowered the barrier to conducting sophisticated environmental analyses, especially in resource-limited regions.

As a result, GEE has seen exponential adoption across the remote sensing and Earth observation communities. Its applications span a wide range of environmental domains, including deforestation tracking, land cover classification, drought assessment, wildfire monitoring, and vegetation carbon stock estimation.

Several recent reviews have examined related aspects of remote sensing for vegetation and carbon monitoring. For instance, Tamiminia et al. (2020) conducted a meta-analysis of Google Earth Engine (GEE) applications across geospatial disciplines, Velastegui-Montoya et al. (2023) mapped global trends and usage patterns of and Ma et al. (2024) synthesized multi-sensor advances in above-ground biomass estimation. However, none of these studies specifically synthesized how GEE-based NDVI approaches have been applied to monitor vegetation carbon stocks at the global scale. This review therefore fills a methodological and thematic gap by integrating bibliometric and remote-sensing perspectives to assess scientific progress, geographic distribution, and policy relevance in carbon monitoring research. See also Parag et al. (2024) for a systematic review of SAR-based biomass monitoring in agriculture, which reinforces methodological gaps relevant to carbon assessments.

Despite the growing application of GEE and NDVI in carbon stock estimation, the evolution of research trends in this field remains largely undocumented. While numerous studies estimate biomass and carbon storage using these tools (Mariano Neto et al., 2024; Faria et al., 2024), few have analyzed the broader scientific structure: Who are the leading contributors? What methods and data sources are most common? Where are the geographic and thematic gaps?

Bibliometric analysis provides a robust methodology to explore these questions. It enables researchers to map publication trends, collaboration networks, thematic focus, and methodological innovations (Aria and Cuccurullo, 2017; Bornmann and Mutz, 2015; Dias et al., 2023).

Although bibliometric reviews have addressed topics such as carbon credits, vegetation phenology, and wetland monitoring, no prior study has focused specifically on vegetation carbon stock monitoring using GEE—especially one that integrates bibliometric methods with insights from remote sensing.

This study addresses that gap by conducting a systematic bibliometric review of 91 peer-reviewed articles published between 2017 and early 2024. The dataset was assembled using a structured search in the Web of Science database, which was selected for its standardized metadata, high indexing quality, and strong coverage of environmental and remote sensing journals (Falagas et al., 2008; Birkle et al., 2020). Although other databases such as Scopus and Google Scholar offer broader coverage, they include inconsistent metadata formats and duplicate entries, which can compromise the accuracy of bibliometric analyses. The analysis was carried out using the Bibliometrix R package and its web interface, Biblioshiny (Zupic and Čater, 2015; Donthu et al., 2021).

This review is guided by the following research questions:

- What are the main publication trends, thematic focuses, and methodological approaches in GEE-based carbon stock monitoring?
- Who are the most active countries, institutions, and authors contributing to this research field?
- Which satellite platforms, data sources, and vegetation indices are most frequently used?
- How are international collaboration networks structured, and where do geographic or institutional gaps persist?
- What opportunities and challenges exist for advancing this research area in the coming years?

By answering these questions, this study offers both a retrospective view of how the use of GEE and NDVI in carbon stock monitoring has evolved and a prospective agenda for future research. It also identifies opportunities for enhancing inclusivity, technological capacity, and scientific collaboration—especially in underrepresented regions such as Sub-Saharan Africa and Southeast Asia, where vegetation monitoring is essential but often under-resourced (Xu et al., 2016; Venkatappa et al., 2019; Alvarez and Govind, 2025).

Our findings will be of interest to researchers in remote sensing, climate science, forest ecology, and geospatial data science, as well as to policymakers and organizations seeking to enhance carbon monitoring systems through scalable, data-driven approaches.

2. Materials and methods

This study employs a bibliometric approach to systematically analyze global research trends in vegetation carbon stock monitoring using Google Earth Engine (GEE) and NDVI-based remote sensing methods. The methodology was structured in three main phases: (1) data retrieval and curation, (2) bibliometric analysis using specialized tools, and (3) synthesis and visualization of trends related to scientific output, authorship, thematic evolution, and collaboration networks. The methodological design follows best practices in bibliometric studies (Aria and Cuccurullo, 2017; Donthu et al., 2021; Garcia et al., 2025) and was adapted specifically for research in environmental monitoring and remote sensing.

2.1. Data source and search strategy

The Web of Science (WoS) Core Collection was selected as the data source due to its comprehensive coverage of high-impact journals in environmental and geospatial sciences (Birkle et al., 2020; Nogueira et al., 2024). A structured search was conducted using the Boolean string: TS = ("carbon" AND "NDVI" AND "Google Earth Engine"). Although multiple databases (e.g., Scopus, IEEE Xplore, and Google Scholar) could have been used, this study selected the Web of Science (WoS) as the exclusive data source because of its standardized metadata structure, peer-reviewed content, and high citation indexing accuracy. This platform ensures the inclusion of validated and replicable scientific records, facilitating transparent bibliometric analysis. Its strong coverage of environmental, geospatial, and Earth observation journals makes it particularly appropriate for the scope of this study. The search targeted peer-reviewed journal articles published in English between January 2017 and December 2024, a period that reflects the post-public release expansion of GEE usage in scientific research (Gorelick et al., 2017; Kumar and Mutanga, 2018). To ensure methodological consistency, only original research articles were included. Reviews, editorials, and conference proceedings were excluded from the analysis (Bornmann and Mutz, 2015; Dias et al., 2023).

2.2. Data curation and preprocessing

From this search, 92 records were exported in BibTeX format for analysis in Biblioshiny. After excluding one non-English record, 91 studies remained for full bibliometric analysis. Because the search query was conceptually focused and precise, no additional duplicates or irrelevant records were identified. All metadata were checked individually to ensure accuracy and consistency across the dataset, maintaining compatibility with Biblioshiny and reliability for subsequent analysis.

The eligibility criteria required that each study present an empirical or analytical connection between the Normalized Difference Vegetation Index (NDVI) and the Google Earth Engine (GEE) for the estimation or analysis of vegetation carbon dynamics. Studies employing GEE or NDVI in unrelated environmental domains—such as hydrological modeling, urban mapping, or soil assessment—were excluded, as were those focused solely on algorithm testing or machine-learning validation without a carbon-related objective. This approach ensured methodological coherence and thematic alignment with the goal of mapping global research trends on GEE-based NDVI carbon monitoring.

2.3. Bibliometric tools and analysis

Bibliometric analysis was conducted in RStudio (version 4.3.3) using the Bibliometrix R package and its Biblioshiny graphical interface (Aria and Cuccurullo, 2017; Narayana Prasad and Kalla, 2021). Keyword co-occurrence networks were generated to map conceptual linkages and thematic structures across the research domain. The analysis employed fractional counting with a minimum threshold of three keyword occurrences, ensuring that only statistically robust terms were retained for visualization. This approach enabled the identification of core research clusters and emerging thematic fronts (Van Eck and Waltman, 2010; Tsilika, 2023), offering a quantitative perspective on the evolution of conceptual relationships within GEE–NDVI carbon studies. These tools enabled the processing, exploration, and visualization of bibliographic metadata.

The overall workflow is illustrated in Fig. 1and includes the following analytical components:

- Performance analysis — annual publication trends, most productive authors, journals, institutions, and countries;
- Keyword analysis — examination of word frequency patterns and visualization through word clouds to highlight dominant concepts and methodological focus areas;
- Scientific mapping analysis of co-authorship relationships and country-level collaborations, generated through the *Collaboration Network* function in Biblioshiny (Dias et al., 2023; Donthu et al., 2021);
- Thematic evolution exploration of emerging topics and conceptual shifts within GEE, NDVI carbon studies over time;
- Geographic mapping spatial representation of national contributions and collaboration intensity using Biblioshiny's built-in visualization tools (Nogueira et al., 2024).

2.4. *Remote sensing classification and application mapping*

To bridge the bibliometric findings with remote sensing practices, we manually reviewed each selected article to extract the satellite platforms, sensor types, and vegetation indices employed—such as Landsat 8, MODIS, Sentinel-2, NDVI, and EVI.

These remote sensing elements were then categorized into broader application areas:

- Biomass estimation (Faria et al., 2024; Wang et al., 2023)
- Net Primary Productivity (NPP) modeling (Rodigheri et al., 2024)
- Forest degradation detection (Bondur et al., 2022)
- Land-use/land-cover change linked to carbon (He et al., 2022)

This step allowed us to identify which types of data are most frequently applied in GEE-based vegetation carbon monitoring, and how these are distributed across distinct analytical objectives within the environmental sciences.

2.5. *Methodological synthesis of carbon estimation models*

In addition to bibliometric procedures, the methodological synthesis of the reviewed literature considered the dominant modeling approaches used for forest carbon stock estimation within GEE-based workflows. The analyzed studies predominantly apply empirical regression models linking NDVI and related vegetation indices to aboveground biomass and carbon density, due to their operational simplicity and widespread adoption (Laurin et al., 2017; Chang et al., 2024). More recent contributions increasingly employ machine-learning techniques, such as Random Forest and Support Vector Machines, to capture non-linear relationships and improve predictive performance in structurally complex forests (Qi et al., 2022; Mariano Neto et al., 2024). In parallel, multivariate and multi-sensor strategies have emerged, integrating optical indices with additional spectral or structural information to enhance carbon stock assessments (Bondur et al., 2024). This synthesis provides methodological context for interpreting the trends and results discussed in the subsequent sections.

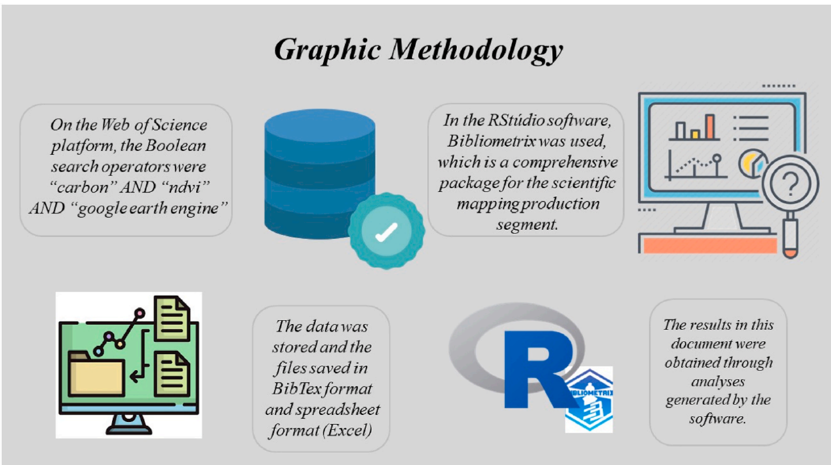

Fig. 1. Workflow diagram for bibliometric analysis of vegetation carbon monitoring studies using NDVI and Google Earth Engine. The process includes data extraction, cleaning, processing in Bibliometrix/Biblioshiny, and final visualization and interpretation of trends and networks.

Fig. 2. Annual publication count and citation trends from 2017 to 2024.

Sources	Articles
REMOTE SENSING	14
ECOLOGICAL INDICATORS	5
REMOTE SENSING OF ENVIRONMENT	5
REMOTE SENSING APPLICATIONS-SOCIETY AND ENVIRONMENT	4
EARTH SYSTEM SCIENCE DATA	3
ENVIRONMENTAL MONITORING AND ASSESSMENT	3
INTERNATIONAL JOURNAL OF APPLIED EARTH OBSERVATION AND GEOINFORMATION	3
ENVIRONMENTAL RESEARCH LETTERS	2
FORESTS	2
FRONTIERS IN ENVIRONMENTAL SCIENCE	2

Fig. 3. Top contributing journals based on publication count.

2.6. Limitations and quality assurance

This study presents some inherent limitations that were addressed through deliberate methodological choices. First, relying exclusively on the Web of Science (WoS) database may have excluded relevant studies indexed in other repositories such as Scopus, Dimensions, or Google Scholar. However, WoS was chosen for its consistent metadata structure, rigorous indexing standards, and wide acceptance in bibliometric research (Birkle et al., 2020).

Second, the use of the term "NDVI" in the search string may have introduced a bias toward optical-based vegetation monitoring, potentially excluding studies that focused on alternative indices such as EVI, SAVI, or NPRVI. This decision was intentional, as NDVI remains the most widely adopted index in studies of vegetation carbon estimation (Gamon et al., 1995; Fassnacht et al., 2019).

Finally, to ensure transparency and reproducibility, the entire analysis was conducted using open-source tools, and all R scripts used in Bibliometrix are available upon request. These measures strengthen the scientific robustness and replicability of the study.

3. Results

This section presents the bibliometric and remote sensing content analysis of 91 peer-reviewed articles published between 2017 and 2024 that applied Google Earth Engine (GEE) and NDVI to monitor vegetation carbon stocks. Results are organized according to publication trends, contributor productivity, spatial distribution, thematic evolution, remote sensing platform usage, and research collaboration.

3.1. Publication output and growth dynamics

The number of publications related to GEE-based vegetation carbon stock estimation has increased consistently since 2017. The field has demonstrated growing academic interest, with an estimated annual growth rate of 47 %. In total, 517 authors contributed to the dataset, using 386 distinct keywords. Each article received an average of 15 citations, and together, the works referenced 5283 sources across 53 different journals (Donthu et al., 2021; Aria and Cuccurullo, 2017).

Collaboration patterns were notably strong, with an average of six co-authors per publication. Many of these involved researchers

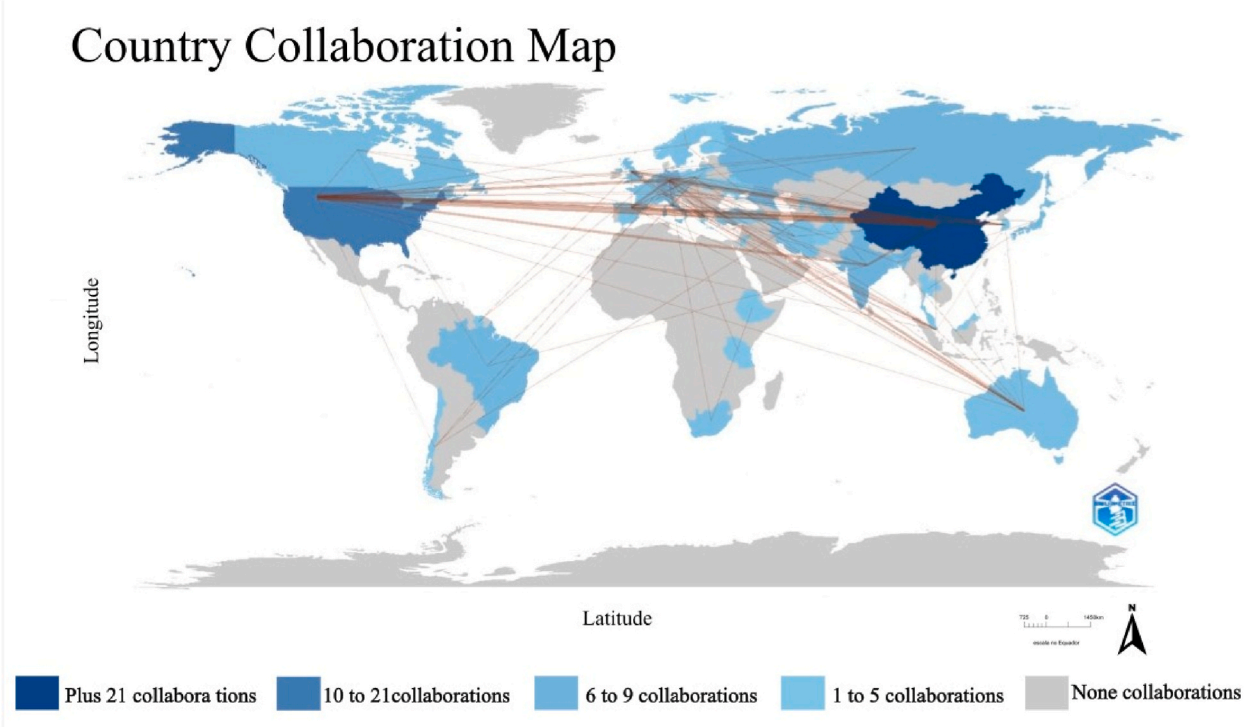

Fig. 4. Country collaboration network based on co-authorship.

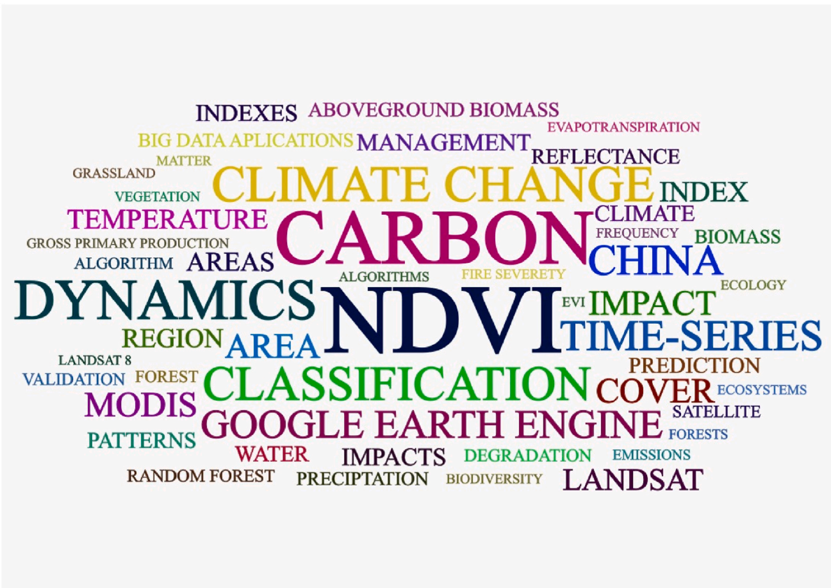

Fig. 5. Word cloud and thematic evolution of keywords (2017–2024).

from different countries, reinforcing the interdisciplinary and global nature of the topic and the increasing reliance on cloud-based geospatial technologies (Gorelick et al., 2017; Kumar and Mutanga, 2018).

3.2. Leading journals and source impact

Among the ten most relevant sources, the journal Remote Sensing is the most prominent, contributing 32 % of the publications in the dataset. It is followed by Remote Sensing of Environment and Ecological Indicators, each accounting for approximately 11 % of the total output. These journals emphasize operational applications of remote sensing for environmental monitoring and carbon estimation. According to Bradford's Law (Nash-Stewart et al., 2012; Zupic and Čater, 2015), they constitute the core zone of scientific productivity in this field—indicating a concentration of relevant contributions within a few specialized outlets (Guimarães et al., 2021).

3.3. Geographic distribution and country-level output

The dataset included author affiliations from ten countries. China was the most productive, contributing the highest number of citations (280), followed by the United States (202) and Brazil. This pattern reflects robust national investments in geospatial infrastructure and scientific output. Leading institutions in these countries include NASA and INPE, which have played central roles in promoting GEE-based carbon monitoring (Wang et al., 2023; Liu et al., 2023; Faria et al., 2024; Bondur et al., 2024).

In contrast, regions such as Sub-Saharan Africa, Southeast Asia, and Central America remain significantly underrepresented. This imbalance reinforces patterns already observed in other bibliometric studies on wetland and vegetation mapping (Igwe et al., 2022; Mandal and Hosaka, 2020), and underscores the persistent geographic asymmetries in access to research infrastructure and visibility in global science.

3.4. Keyword dynamics and thematic evolution

The keyword co-occurrence analysis revealed a strong concentration of terms related to technology and ecology. The most frequent keywords were NDVI, carbon, climate change, biomass, and Google Earth Engine—reflecting the methodological core of studies in this field.

Thematic evolution maps showed a chronological progression in research focus. Between 2017 and 2019, studies clustered around basic carbon–NDVI relationships. From 2020 to 2022, the focus shifted toward integrating GEE with machine learning techniques. More recently, in 2023–2024, there has been a marked increase in studies involving multi-sensor fusion. Emerging keywords such as Sentinel-1, deep learning, and REDD + suggest an increasing alignment with advanced modeling methods and policy-relevant agendas (Rodigheri et al., 2024; Bondur et al., 2022; Ahmadi et al., 2023; Duchelle et al., 2018).

3.5. Remote sensing platforms and application types

Manual classification of the selected articles revealed that MODIS, Landsat 8, and Sentinel-2 were the most commonly employed satellite platforms within GEE workflows. This trend is consistent with their widespread use in time-series vegetation analysis and biomass estimation (Anderson et al., 2020; Ghorbanian et al., 2022; Zhang and Fan, 2025). The summarized distribution is as follows Table 1.

Nearly all studies relied on NDVI as the primary vegetation index. Only a minority incorporated alternative indices such as EVI, SAVI, or radar-derived metrics like VH/VV or NPRVI (Laurin et al., 2017; Bondur et al., 2024). This reflects a methodological preference for optical sensors, although it may limit applicability in persistently clouded regions or complex forest canopies.

3.6. Variability in accuracy across forest types and models

The reviewed literature indicates substantial variability in the accuracy of forest carbon and biomass estimates derived from remote sensing data. Reported performance metrics, such as R^2 and RMSE, differ markedly according to forest type, sensor characteristics, and modeling strategy. Studies comparing Landsat- and MODIS-based applications consistently report variations in estimation accuracy associated with spatial resolution, temporal aggregation, and vegetation structure (Dahal et al., 2021; Wang et al., 2021). In addition, NDVI-based approaches exhibit higher predictive accuracy in open or less structurally complex vegetation, while increased uncertainty is commonly observed in dense forest formations (Dias et al., 2023; Sergio et al., 2016; Zezhong et al., 2025). These findings demonstrate that the accuracy of forest carbon estimation is strongly context-dependent and influenced by both ecological conditions and methodological choices.

Long-term analyses indicate that the temporal depth of satellite-derived vegetation indices plays a critical role in improving model (Kato et al., 2020), reliability, multi-decadal time series substantially outperforming short-term summaries in predicting carbon stocks. At larger spatial scales, assessments integrating extensive forest inventory data with Landsat-derived phenological metrics have demonstrated enhanced robustness, and reduced uncertainty (Venkatappa et al., 2019), underscoring the importance of harmonizing

Table 1
Commonly employed satellite platforms within GEE.

PLATFORM	% OF STUDIES	APPLICATION FOCUS
MODIS	29 %	Time-series biomass and productivity mapping
LANDSAT 8	40 %	Forest structure, carbon degradation analysis
SENTINEL 1	26 %	Agricultural carbon stock, NDVI trend detection
SENTINEL 2	5 %	Radar fusion and early-stage forest disturbance

ground observations and remotely sensed data to improve the accuracy and consistency of forest and soil carbon estimates across heterogeneous landscapes (Cao et al., 2021).

3.7. Saturation effects in optical-based carbon estimation

A recurring limitation identified across the analyzed studies is the saturation effect associated with optical vegetation indices, particularly NDVI, in high-biomass and structurally complex forests. Several investigations report that NDVI exhibits reduced sensitivity beyond moderate canopy closure, leading to systematic underestimation of biomass and carbon stocks in dense tropical and boreal ecosystems (Laurin et al., 2017). This limitation is also evident in large-scale biomass products, where optical signal saturation contributes to increased uncertainty in regions with closed canopies and high carbon density (Avitabile et al., 2016). Evidence from Arctic and boreal environments further demonstrates that the strength of NDVI–biomass relationships declines as vegetation density increases, reinforcing saturation as a persistent constraint in optical-based vegetation carbon mapping (Berner et al., 2018).

Saturation effects are common in optical remote sensing imagery, particularly in areas of dense vegetation. In contrast, radar-based indices offer important advantages, as they enable image acquisition under all-weather conditions and provide enhanced sensitivity to vegetation structural characteristics. Radar data therefore represent a valuable alternative for improving vegetation analysis, however, radar information alone is often insufficient for accurate carbon quantification. Optimal results are generally achieved by integrating radar data with spectral or hyperspectral observations, which allows complementary information to be exploited (Chang et al., 2024; Lin et al., 2024).

3.8. Institutional collaboration and network structure

The average number of authors per article was 5.68, with most publications involving 3 to 7 co-authors—an indicator of strong interdisciplinary collaboration (Nogueira et al., 2024). Among the most central institutions in the global co-authorship network were the Chinese Academy of Sciences, NASA, and Brazil's INPE, reflecting the leadership of countries with established remote sensing programs.

However, the analysis also revealed a persistent imbalance in collaboration patterns. Most international partnerships were concentrated in China–Europe and US–Europe axes, while South–South collaborations remained limited and fragmented (Dias et al., 2023). This asymmetry reinforces concerns about the marginal participation of institutions located in carbon-rich but underrepresented tropical regions, such as parts of Africa, Southeast Asia, and South America (Venkatappa et al., 2019). Addressing this gap will be essential for strengthening global research equity and scientific inclusion.

3.9. Gaps and future opportunities

The bibliometric and thematic analysis revealed several persistent gaps in the current research landscape:

- Geographic underrepresentation of carbon-rich regions such as Africa and Southeast Asia, where research capacity remains limited despite ecological importance (Xu et al., 2016; Ghorbanian et al., 2022);
- Limited integration of field-based validation, with only 14 % of studies incorporating in-situ measurements from biomass plots or carbon flux towers (Laurin et al., 2017);
- Scarce connection to policy instruments such as REDD+ and the Sustainable Development Goals (SDGs), even though GEE outputs could support national reporting and mitigation planning (Ahmadi et al., 2023).
  To address these shortcomings, future research should prioritize efforts to expand monitoring initiatives in neglected regions, integrate GEE-based workflows with ground validation and AI models, and develop accessible, multilingual training resources that reduce technical and educational barriers in low-income contexts.

These directions are essential not only for improving methodological rigor and geographic inclusivity but also for strengthening the policy relevance of scientific research on vegetation carbon monitoring.

4. Discussion

The growing number of publications using Google Earth Engine (GEE) and NDVI reflects not only increasing academic interest, but also a broader transformation in environmental monitoring practices. The rise of cloud computing and the availability of open-access satellite imagery have enabled more scalable, reproducible workflows for vegetation and carbon analysis—supporting the maturation of a new, data-intensive scientific domain (Gorelick et al., 2017; Kumar and Mutanga, 2018).

This surge is likely influenced by global climate policy frameworks—such as the Paris Agreement and REDD+—which have elevated the need for accessible, high-resolution tools for carbon monitoring. GEE's integration into scientific workflows aligns with these priorities, offering technical solutions for monitoring vegetation dynamics at both national and sub-national levels (Duchelle et al., 2018).

While publication frequency has increased, citations per document remain moderate, suggesting that the field is still maturing. A possible explanation is the relatively recent integration of GEE into academic workflows and the lack of widespread standardized protocols for biomass or carbon estimation using NDVI.

4.1. Sensor selection and methodological shifts

The frequent use of MODIS, Landsat 8, and Sentinel-2 reflects a methodological preference for sensors that balance spatial resolution with temporal frequency. These platforms have been widely adopted for monitoring vegetation patterns across diverse biomes. MODIS, in particular, is suited for long-term trend analyses due to its high temporal resolution (Mandal and Hosaka, 2020), while Sentinel-2 has gained traction for detecting fine-scale carbon dynamics (Faria et al., 2024).

Despite their effectiveness, these sensors rely heavily on optical data, which can limit performance in persistently clouded or structurally complex environments (Anderson et al., 2020). This highlights the need for integrating complementary data sources.

Recent years have seen a methodological transition toward multi-sensor fusion—particularly combining Sentinel-1 radar data with optical imagery—and the application of machine learning techniques such as random forest, support vector machines, and deep learning (Rodigheri et al., 2024; Bondur et al., 2022). These approaches have improved classification accuracy and model robustness, especially in heterogeneous landscapes. The rise of keywords like "Sentinel-1" and "machine learning" after 2020 reflects this trend toward data-intensive, automated analyses.

However, the reliability of these models remains constrained by the lack of in-situ validation. Few studies incorporated field-based biomass plots or carbon flux towers, which are critical for calibrating remote estimates (Laurin et al., 2017; Bondur et al., 2024). Strengthening hybrid workflows that integrate GEE outputs with ground truth data is therefore essential—not only for scientific accuracy, but also for expanding the applicability of these methods across different ecological and infrastructural contexts.

4.2. Geographic inequity in research

The global distribution of research on GEE-based vegetation carbon monitoring is markedly uneven. Countries such as China, the United States, and Brazil account for the majority of publications and citations, whereas carbon-rich regions like Central Africa and Southeast Asia remain severely underrepresented in both scientific output and collaborative networks (Xu et al., 2016; Venkatappa et al., 2019).

This imbalance reflects not only ecological neglect, but deep structural constraints: limited access to geospatial infrastructure, inadequate internet connectivity (a critical requirement for GEE), and insufficient training in cloud-based remote sensing tools (Nogueira et al., 2024). Furthermore, collaborative ties tend to concentrate among well-resourced institutions, perpetuating North–South disparities in knowledge production.

These findings mirror trends observed in other remote sensing domains, such as wetland mapping (Igwe et al., 2022), and underscore the urgency of investing in inclusive scientific ecosystems. Promoting open-access GEE training, regional capacity-building initiatives, and equitable South–South research partnerships is essential to ensure that global carbon monitoring efforts are both scientifically robust and socially just.

4.3. Gaps in policy integration

A key finding of this review is the persistent disconnect between academic research and climate policy frameworks. Although Google Earth Engine (GEE) offers robust capabilities for supporting national carbon accounting—including REDD+, NDCs, and the UN Sustainable Development Goals (SDGs)—only a small portion of the analyzed studies explicitly referenced these policy instruments (Ahmadi et al., 2023; Duchelle et al., 2018).

This lack of policy framing undermines the practical relevance of technically sound research, limiting its contribution to climate governance and mitigation planning. To strengthen the policy impact of future studies, researchers should aim to: (i) link GEE-derived carbon estimates to REDD + baselines or Tier 2/3 national GHG inventories; (ii) incorporate uncertainty assessments aligned with IPCC guidelines; and (iii) develop accessible visualization tools and dashboards to facilitate decision-making by policymakers.

4.4. Future directions

Building on the patterns and gaps identified in this review, we propose four strategic directions to advance research on GEE-based carbon monitoring:

First, future studies should diversify input data beyond NDVI by incorporating radar (e.g., Sentinel-1), hyperspectral (e.g., PRISMA), and LiDAR (e.g., GEDI) sources. These sensors provide structural information on canopy height, density, and moisture content, enabling more accurate biomass estimations than NDVI alone (Ghorbanian et al., 2022).

Second, fostering interdisciplinary collaboration between ecological modelers, remote sensing analysts, and policy experts can generate integrated approaches that are both methodologically robust and actionable. Third, validation protocols must be strengthened by utilizing open-access field datasets—such as ForestPlots.net and FLUXNET—and national forest inventory databases. These resources are vital for calibrating remote sensing models and improving estimation accuracy. In this regard, exploring carbon stock monitoring using GEE is essential, particularly through emerging tools such as satellite embeddings. These allow for new research avenues into how environmental patterns relate to diverse spatial elements (Alvarez et al., 2025).

Finally, promoting equitable access to remote sensing tools requires targeted training programs in low-income regions. This includes organizing GEE workshops, producing multilingual documentation, and expanding financial support for scientific mobility and participation in international events.

In summary, while GEE has significantly democratized access to carbon monitoring, important challenges remain in achieving geographic inclusivity, methodological rigor, and policy integration. Bridging these gaps is essential for the remote sensing community to contribute meaningfully to global climate mitigation and sustainable land-use planning.

5. Conclusion

This review offers a comprehensive bibliometric and thematic analysis of global research trends in vegetation carbon stock monitoring using Google Earth Engine (GEE) and NDVI, based on 91 peer-reviewed articles published between 2017 and early 2024. The findings reveal a rapidly expanding field fueled by advances in cloud computing, open-access satellite imagery, and machine learning techniques. Most studies rely on well-established platforms such as MODIS, Landsat, and Sentinel-2, with a growing movement toward multi-sensor integration and AI-driven modeling. While scientific output has increased markedly—particularly in China, the United States, and Brazil—substantial regions of the Global South, including Africa and Southeast Asia, remain underrepresented despite their ecological significance.

The thematic evolution of the literature reveals a shift from basic NDVI applications toward more complex frameworks involving biomass modeling, forest degradation detection, and climate assessment. However, persistent challenges include the lack of in-situ validation, weak alignment with policy instruments such as REDD+ and the SDGs, and limited South–South collaboration.

To address these issues and enhance the impact of remote sensing research on global sustainability agendas, we recommend: (i) increased investment in capacity-building and open-access training in underserved regions; (ii) stronger integration of policy-relevant indicators and uncertainty metrics; and (iii) expansion of validation protocols through ground-based data sources. As climate change accelerates, scalable, inclusive, and policy-relevant monitoring frameworks like GEE will be essential in guiding land-use decisions, conservation planning, and carbon management. This review provides a structured foundation to advance such efforts through collaborative, equitable, and methodologically rigorous remote sensing science.

CRediT authorship contribution statement

Adriana Bilar Chaquime dos Santos: Writing – original draft, Resources, Methodology, Data curation. **Patricia Pedrozo Lamberti:** Resources, Data curation. **Deimison Rodrigues Oliveira:** Resources, Data curation. **Micaella Lima Nogueira:** Resources, Data curation. **Cesar Ivan Alvarez:** Writing – review & editing, Writing – original draft. **Reginaldo Brito da Costa:** Supervision.

Availability of data and material

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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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.

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Data availability

Data will be made available on request.

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