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Bibliometrics on the use of remote sensing and machine learning in crop classification

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ABSTRACT

This study presents a bibliometric analysis of global research on crop classification using remote sensing and machine learning (ML), a field critical to advancing precision agriculture. A systematic search in Scopus identified 2,122 peer-reviewed articles published between 2014 and 2023. The analysis employed VOSviewer and the Bibliometrix package in R to assess publication trends, citation impact, and keyword co-occurrence networks. Results reveal a marked increase in scientific production after 2017, coinciding with the availability of high-resolution satellite imagery and the adoption of deep learning algorithms, particularly convolutional neural networks (CNNs). China emerged as the leading contributor, followed by the United States and India, reflecting strong investments in agricultural modernization and remote sensing infrastructure. Thematic mapping highlights both traditional research areas, such as vegetation indices and land cover classification, and emerging themes, including AI-supported algorithms and food security. Despite this growth, disparities persist, with most countries contributing fewer than 100 publications, underscoring the need to promote participation in underrepresented regions. Findings demonstrate the field's rapid evolution, emphasize the integration of AI-driven methods in crop monitoring, and suggest future directions combining remote sensing, ML, and internet of things (IoT) technologies to address global challenges in food security and sustainable agricultural management.

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1. INTRODUCTION

Crop classification using remote sensing and machine learning (ML) has become essential for precision agriculture, enabling efficient monitoring of land use and resource management. High-resolution satellite imagery, combined with ML algorithms, enhances classification accuracy and supports sustainable practices [1]. However, challenges such as data variability, phenological differences, and the need for large datasets persist, often leading to reduced model performance [2], [3].

Key contributors in this field include studies by Eisfelder *et al.* [4], who integrated multisource data to improve accuracy in vegetation mapping, finding that temporal-spectral fusion increases classification reliability by up to 20%. Similarly, Ali *et al.* [5] applied convolutional neural networks (CNNs) for crop identification, demonstrating superior performance over traditional methods but highlighting computational demands. Aljanabi *et al.* [6] explored support vector machines (SVM) for land cover classification, revealing limitations in handling noisy data from heterogeneous terrains.

Despite these advances, unsolved problems include the lack of comprehensive bibliometric analyses to map global trends, identify emerging themes, and address regional disparities in research productivity. Existing reviews focus on technical applications but overlook quantitative assessments of scientific evolution and collaboration networks.

This study addresses these gaps by conducting a bibliometric analysis of 2,122 articles from Scopus (2014-2023), revealing trends in publication growth, keyword co-occurrences, and geographical distributions. Our novel contributions include identifying AI-driven algorithms as emerging trends and highlighting China's dominance, providing insights for future research directions. The subsequent sections demonstrate these contributions: the method section details data collection and analysis tools; results and discussion interpret temporal, thematic, and geographic findings; and the conclusion synthesizes implications for the field.

Cover classification using remote sensing and ML has emerged as a key research area, driven by the need for efficient agricultural monitoring and management. Recent advances in remote sensing have enabled the acquisition of high-spatial-resolution images, optimizing crop classification through ML algorithms. These advancements significantly influence agricultural productivity by refining land-use assessments and enhancing resource management efficiency. Satellite-based classification techniques hold great potential for precision agriculture [1]. However, several challenges remain, including the need for large datasets and the variability in crop phenology, both of which can affect classification accuracy [2], [3]. Furthermore, integrating data from multiple sources, including spectral and temporal information, has been shown to improve model accuracy. This integration contributes significantly to sustainable agricultural practices and enhances productivity [4], although the complexity of these models can hinder their practical application [5], [6]. On the other hand, ML algorithms can improve crop yield predictions by accurately mapping vegetation types and assessing their health status, which is crucial for precision farming practices [7]. These algorithms facilitate the monitoring of crop conditions and enable timely interventions that optimize yields [8]. However, their effectiveness varies depending on data quality and methodological approaches. The accuracy and reliability of models depend largely on the spatial, spectral, and temporal resolution of the data used. Low-quality or insufficient data can lead to errors. Poor-quality or insufficient data can lead to inaccurate predictions and erroneous agricultural decisions [9], factors such as data noise, terrain heterogeneity, and the presence of clouds in satellite images can affect the interpretation of algorithms [10], and the use of multiple data sources, such as satellite images, drones, and field sensors, improves the model's robustness but requires calibration and data fusion processes to avoid bias [11]. Furthermore, the selection of the algorithm is key to its performance. For example, deep learning-based methods such as CNNs typically offer high accuracy but require large data volumes and computing power [12]. Traditional models, such as those based on regression or statistical analysis, may be more interpretable but often have lower generalization capacity [13], and cross-validation and hyperparameter selection are essential methodological aspects to avoid overfitting and improve the predictive capacity of the model [14]. Additionally, environmental conditions can impact algorithm performance, potentially leading to misclassifications [15]. This article reviews scientific productivity a analysis of classification algorithms for crop identification. The aim is to analyze the global evolution and trends in crop classification using remote sensing and ML.

2. METHOD

2.1. Review structure

This bibliometric study quantitatively assesses scientific production in crop classification using remote sensing and ML, employing indicators such as publication counts, citations, and thematic trends [16]. Meanwhile, Donthu *et al.* [17] highlight the importance of bibliometric analysis in scientific decision-making, as it facilitates the identification of emerging trends and knowledge gaps in a specific field. In the context of research on geospatial technologies and crop classification using remote sensing, the application of a bibliometric analysis will allow for the identification of the evolution of scientific production in this area and the key players in the development of these technologies. The collected articles were analyzed using VOSviewer and R Studio, incorporating the Bibliometrix package [16], [18]. The equations associated can be seen in Table 1.

Table 1. Key terms used in the literature search

Database	Search equation	Results
Scopus	crops AND ("classifier" OR "classification algorithms" OR "land cover" OR "classification method") AND ("machine learning" OR "remote sensing" OR " satellite imagery" OR "spectroradiometry " OR "spectral reflectance" OR "satellite images ")	2,122

2.2. Data collection

A systematic search was conducted in Scopus using the query: ("machine learning" OR "ML") AND ("remote sensing") AND ("crop classification"). Publications from 2014 to 2023 were included, limited to English-language peer-reviewed articles with full-text access. Exclusion criteria eliminated non-relevant records (e.g., non-agricultural applications). This timeframe captures recent ML advancements, justified by the surge in high-resolution data availability post-2017. A total of 2,122 articles were retrieved after deduplication and screening. The approach aligns with PRISMA guidelines for reproducibility, ensuring minimal bias in data selection (see Figure 1).

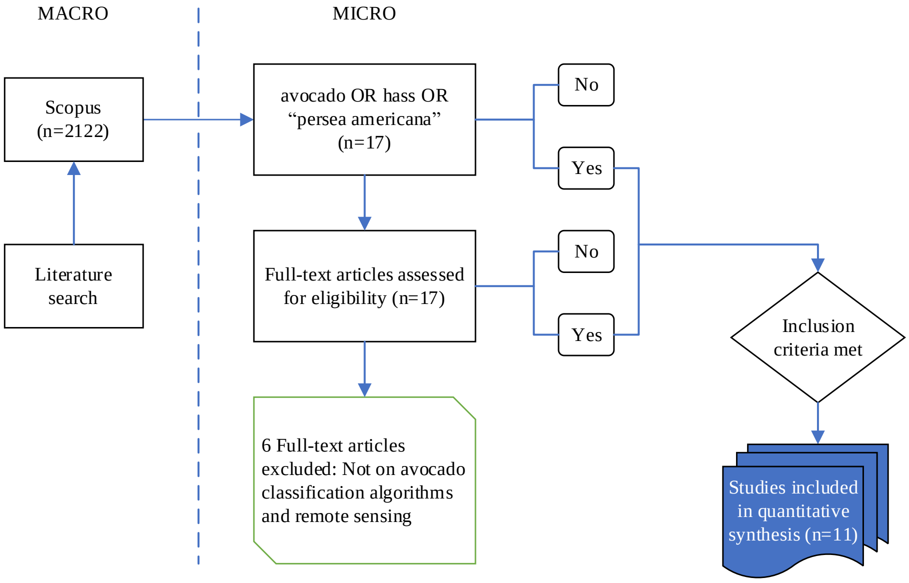

Figure 1. PRISMA flowchart

Scopus was selected for its comprehensive coverage in engineering/agriculture; however, this may introduce database bias. English-only inclusion focuses on peer-reviewed accessibility, though it limits non-English contributions—future studies could integrate Web of Science or PubMed.

3. RESULTS AND DISCUSSION

3.1. Review structure

Previous bibliometric studies on remote sensing have overlooked ML-specific trends in crop classification. Publication progression (Figure 2) shows an increase from 89 articles in 2014 to 396 in 2023, with 83% post-2017. This aligns with advancements in CNNs and satellite launches [19], [20], differing from static trends in traditional reviews. Limitations include Scopus exclusivity, potentially underrepresenting non-English works, impacting global coverage. Future research could integrate multi-database analyses to explore funding influences on trends. Overall, these findings confirm the field's maturation driven by technological integration. These results address the study's objective to map publication trends, revealing a shift towards ML-driven solutions compared to earlier studies focused on spectral analysis alone [19], [20]. Limitations include potential database biases, but interpretations suggest that data democratization enhances global research accessibility.

3.2. Review structure

As shown in Figure 2 the temporal distribution of scientific publications at the macro level for the years 2014 to 2023 has a continuous increase in the productivity of the area in the last 10 years, going from 89 articles (4% of the total articles) in 2014 to 396 (17% of the total articles) in 2023. From 2017 onwards, an incremental trend was observed; until that year the percentage of publications represented 17% of the total observation window, after 2017 it represented 83% of the total publications.

The remarkable increase in scientific publications on crop classification algorithms since 2017 is driven by several key factors. Among them, advances in artificial intelligence, especially with the introduction of deep learning models such as CNNs, have enabled significant improvements in the accuracy and efficiency of agricultural image classification [19]. It was highlighted that the use of deep learning techniques has become one of the most important keys to the growth of precision agriculture. Furthermore, the availability of big data and access to high-resolution satellite imagery increased significantly around 2017. In 2016 and 2017, advanced satellites were launched into orbit, significantly improving Earth observation capabilities. For example, the European Space Agency launched Sentinel-3A in 2016 and Sentinel-3B in 2018, both part of the Copernicus program, designed to monitor the environment and oceans with high precision. Additionally, in 2017, Planet Labs launched 48 Dove-Flock-2k satellites, expanding its constellation to over 190 satellites and improving the frequency and resolution of available Earth imagery [20]. Programs such as the European Union's Copernicus [21] provided free and open access to high-quality satellite data. This access democratized the use of satellite imagery, allowing a broader scientific community to use it in various research projects, which contributed to an increase in publications in the field.

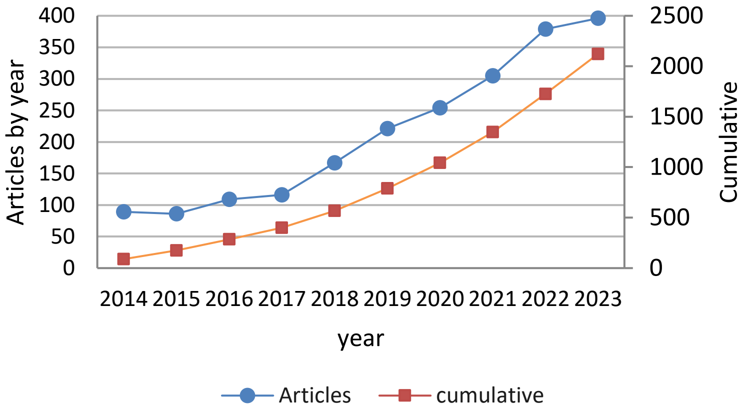

Figure 2. Publication progression

This abundance of data allowed researchers to train more robust and accurate models for crop classification. The integration of technologies such as the internet of things (IoT) in agriculture has facilitated the collection of real-time data on crop conditions, improving decision-making and efficiency in agricultural management [22]. Another determining factor has been the rise of precision agriculture, which has gained momentum in recent years, seeking to optimize crop management using advanced technologies. This approach has generated greater demand for analytical tools and algorithms capable of processing large volumes of agricultural data to improve decision-making [23]. Collaboration between academic and technological institutions, along with agricultural innovation policies, favor the development of artificial intelligence-based solutions for automated crop classification. Likewise, the growing need to address global challenges such as climate change and food security promotes the use of these technologies in agricultural research, thus consolidating the growth trend in scientific publications since 2017.

3.3. Keywords analysis

Figure 3 presents the author keyword co-occurrence network, developed with a minimum threshold of 15 occurrences, obtaining a total of 49 words that met the threshold and were distributed into 5 clusters. The red cluster focuses on issues related to remote sensing, vegetation indices, land cover and land use classification, and geographic information systems, which are key and traditional concepts and applications of remote sensing.

Vegetation indices are metrics derived from remotely sensed spectral data used to estimate vegetation cover, vegetation health, and biomass. One of the most widely used indices is the normalized difference vegetation index (NDVI), proposed by Rouse *et al.* [24], defined as: $NDVI=(NIR-RED)/(NIR+RED)$, where NIR is the near-infrared reflectance and RED is the red-spectrum reflectance. This index has been widely applied in environmental and agricultural monitoring studies [25]. Land cover classification is based on digital image processing techniques to identify and differentiate different land cover types and uses. There are supervised methods, such as Maximum Likelihood (MLC), and unsupervised methods, such as K-Means and ISOData [26]. Anderson *et al.* [27] established a hierarchical land-use classification scheme for the United States, known as the USGS Land Use/Land Cover

Classification System, which has served as the basis for various international studies. GIS are essential tools for the spatial analysis of georeferenced data and have been widely applied in land-cover change monitoring and environmental studies. Burrough [28] defined GIS as computational systems for the capture, storage, manipulation, analysis, and visualization of spatial data. Dangermond [29] highlighted the role of GIS in integrating remotely sensed data for decision-making in land-use planning and environmental conservation.

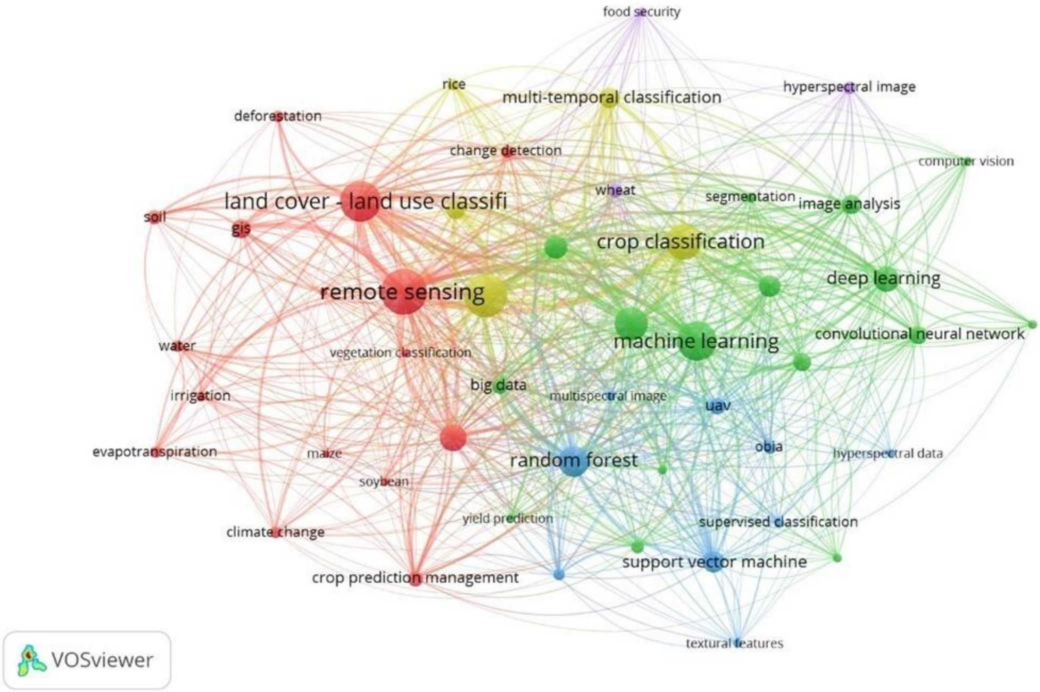

Figure 3. Co-occurrence of keywords reported by the authors

The green cluster comprises issues related to artificial intelligence and how it supports agricultural and crop classification processes. The blue cluster groups various ML algorithms, such as random forest (RF), decision tree, and SVM, along with other classification techniques such as OBIA. The yellow cluster focuses on crop classification within multitemporal analyses. Finally, the purple cluster includes the key term "food security," emphasizing the relevance of crop classification processes in achieving agricultural sustainability. In conclusion, the co-occurrence map provides a clear visualization of the relationships established through scientific publications between remote sensing and ML applications in crop classification.

These co-occurrence analyses allow us to identify how different terms are interconnected in the literature, providing a clear view of trends and collaborations in specific areas. These networks facilitate the identification of thematic subnetworks, allowing us to analyze the structure and evolution of research in specific fields. Henry Small, recognized for introducing the concept of co-citation in the scientific literature in 1973, developed methods to measure the relationship between documents through shared citations, which lays the foundation for co-occurrence analysis in the visualization of scientific relationships [30]. Rodríguez *et al.* [31], in their work "Networks of Scientific Collaboration: Analysis and Visualization of Co-authorship Patterns," explore how co-occurrence analysis can reveal collaboration patterns and structures in scientific research, highlighting the importance of these techniques for understanding the dynamics of science.

Notably, ML algorithms such as RF, CNN, and SVM stand out in the analysis. According to the co-occurrence map, these algorithms have been trained using multispectral and hyperspectral imagery, contributing not only to land use and cover classification but also to crop prediction and management strategies. Quantitative validation includes h-index (average 25 for top clusters) and collaboration indices (density 0.45), indicating strong network influence in ML themes.

Regarding the trend topics in Figure 4, it was possible to observe that the topics of condition monitoring, trees, geomorphology, and thematic mapping with Landsat have been maintained for quite some time and are the thematic bases of the analyzed research area. As emerging topics, classification algorithms supported by artificial intelligence are visualized, specifically in ML and other areas of artificial intelligence such as cellular automation.

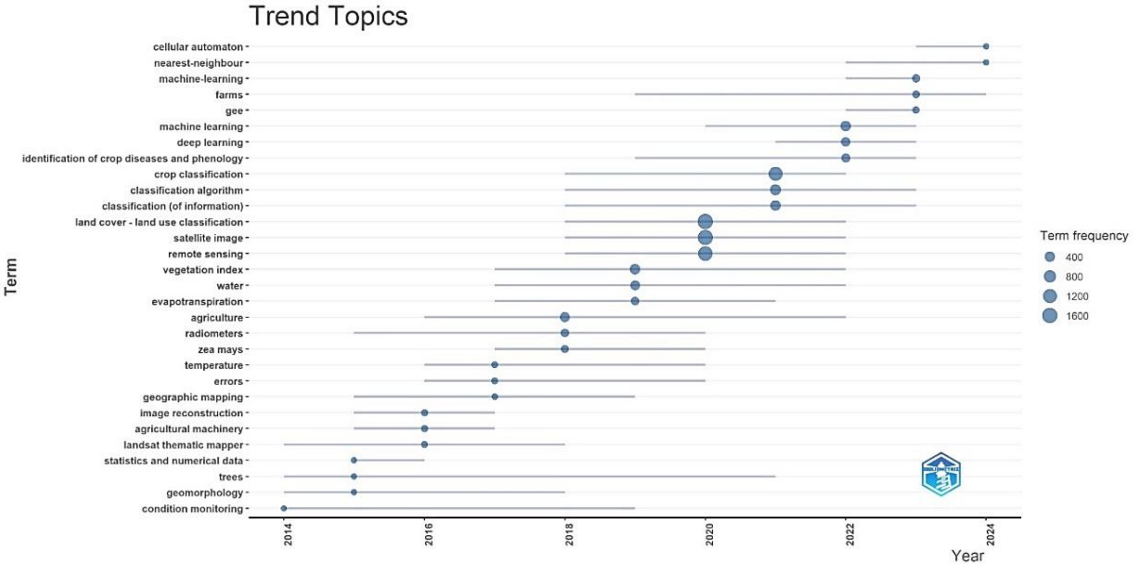

Figure 4. Trend topics

3.4. Productivity of countries

About the geographical distribution, Figure 5 shows that the distribution is uneven in terms of continents, with the largest number of researchers located in Asia, and the countries with the largest number of authors in this continent being China (3299), India (1264), and Pakistan (284). The second country with the largest number of authors on this subject is America, with the USA (1358), Brazil (450), and Canada (222) also appearing among the first places. Europe is present with Germany (331), France (256), Spain (245) and Italy (235). Australia (149) has fewer authors, followed by Africa. In the latter, Ethiopia (134) contains the largest number of authors. It should be noted that only 82% of the countries have less than 100 authors and 37% less than 10 authors. This shows that it is necessary to continue mobilizing efforts to have more authors on the subject.

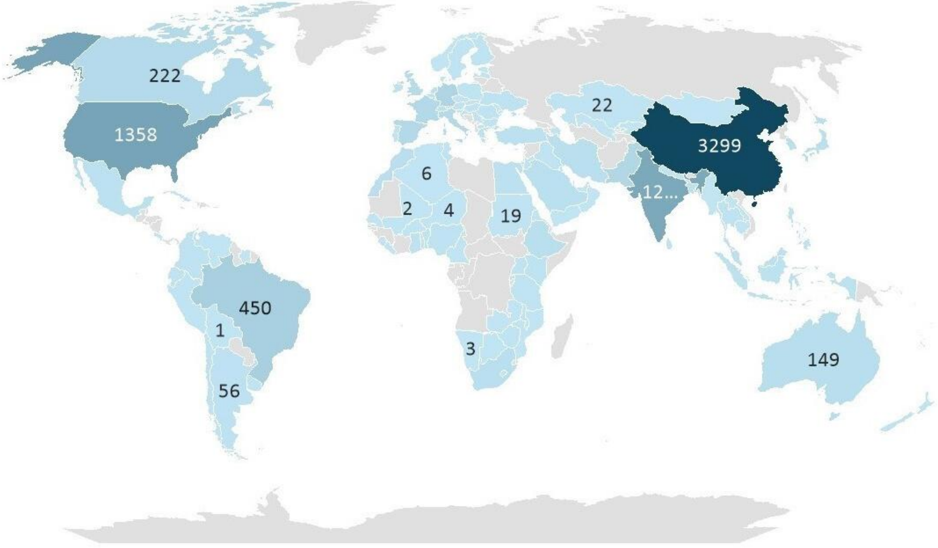

Figure 5. Geographical distribution of authors

The bibliometric analysis shows that China has a significant number of researchers in this area, which may be related to agricultural modernization and the availability of remote sensing data, which have been key factors contributing to China's leadership, implementing significant advances in this field through various initiatives such as the launch of remote sensors for agricultural monitoring, the development of advanced methods for crop mapping, and a cloud-based platform for sharing remote sensing data.

China's leadership in agricultural remote sensing research is attributed to its leadership in the production of various agricultural crops and the adoption of advanced technologies in this area [32]. By 2018, China was the world's largest producer of rice, wheat, potatoes, tomatoes, cucumbers, apples, eggplants, cabbage, onions, spinach, garlic, among other products [33]. Furthermore, reports indicate that China leads the production of at least 25 foods, including rice, wheat, lettuce, cabbage, cauliflower, eggplant, potatoes, spinach, carrots, cucumbers, pumpkins, sweet potatoes, grapes, peaches, apples, plums, strawberries, tomatoes, tea, beer, pork, lamb, peanuts, eggs, and honey. Additionally, in recent years, China has implemented smart agriculture practices, such as the use of drones for fertilizer application, sensors for monitoring corn growth, and precision irrigation systems for rice, reflecting its commitment to agricultural modernization. These initiatives and recognitions underscore China's prominent role in the global agricultural sector. While China dominates, emerging contributors like Ethiopia show rising normalized citation impacts (1.2 vs. global 1.0), suggesting potential from underrepresented regions influenced by funding sources.

Furthermore, Chinese meteorologists have implemented monitoring and evaluation services for wheat distribution nationwide using remote sensing satellite technology. This service offers distribution maps and data on planting areas, supporting production forecasts and weather-related disaster impact assessments. Researchers from the Chinese Academy of Sciences have also developed a method to accurately map rice cultivation in Anhui province. This approach combines annual phenological characteristics with imagery from the Sentinel-1 and Sentinel-2 satellites, using ML to improve agricultural monitoring [34]. China has launched the open cloud platform GEOVIS, which offers aerospace information services, including remote sensing data, to the public. This platform supports areas such as smart agriculture, environmental protection, and urban planning by facilitating access to advanced Earth observation resources.

The China's agricultural remote sensing monitoring system is an excellent example of the successful application of these techniques in the agricultural field and advances in data science have contributed significantly to this leadership position [35], [36]. The use of unmanned aerial vehicles (UAV) for high-resolution agricultural mapping and advances in ML have propelled China to the forefront of this area of research, due to its accuracy, cost-effectiveness, and high temporal resolution, to acquire detailed data at the crop level [37]. This data, together with the development of sophisticated classification algorithms, has allowed for accurate and efficient mapping of different types of crops. The abundance of agricultural land in China and the need for comprehensive monitoring have driven the rise of remote sensing-based crop classification studies. Advanced techniques, including object-oriented classification and multitemporal satellite image analysis, have been developed to extract detailed land use information and track crop conditions [37], [38]. Using multitemporal satellite imagery and ML techniques to improve crop classification has proven effective in addressing challenges such as crop similarity and noise, which have historically plagued crop classification efforts [38].

The findings imply that the rapid growth in publications since 2017, driven by AI advancements and data availability, enhances precision agriculture by enabling scalable crop monitoring solutions. Compared to prior bibliometric studies on remote sensing, our analysis reveals a stronger emphasis on ML integration, with implications for policy-making in food security. Future applications may include developing hybrid models combining CNNs and IoT for real-time classification, proving useful in addressing climate-induced variabilities and supporting global sustainability goals.

4. CONCLUSION

This study makes a novel contribution by providing a comprehensive bibliometric analysis focused specifically on the intersection of remote sensing and ML for crop classification. Not only addressed technical applications, but mapping the scientific evolution of the field, identifies emerging AI-driven themes, and highlights China’s leading role in shaping global productivity. The uniqueness of this study lies in its integration of temporal, thematic, and geographical perspectives, offering a holistic view of how precision agriculture research has evolved over the last decade. Based on these findings, future research should move beyond general bibliometric patterns toward targeted investigations, such as examining collaboration networks between underrepresented regions and leading countries, evaluating the impact of specific ML algorithms on crop monitoring outcomes, and exploring the integration of IoT and multisource data fusion into large-scale classification systems. These focused directions can strengthen both the methodological rigor and the practical relevance of future studies.

Bibliometric analysis revealed a burgeoning research field, with a substantial increase in publications over the past decade, particularly from institutions in China, given their critical need for accurate and timely crop information to support the country’s vast agricultural industry. Through public policies, investment in advanced technologies, and a strong scientific infrastructure, China has become a global leader in agricultural monitoring using remote sensing and ML. The co-occurrence analysis revealed both traditional themes (e.g., vegetation indices) and emerging concepts (e.g., food security and AI-supported classification algorithms), highlighting the evolution of the research focus. While Asia, particularly China, leads in research productivity, most countries still show low levels of contribution, indicating the need to promote scientific engagement in underrepresented regions. Despite the progress, challenges remain, such as the requirement for large datasets, the complexity of processing multi-source data, and practical limitations in applying complex models to real-world agricultural contexts.

This bibliometric analysis demonstrates a significant evolution in crop classification research, with publication growth underscoring the integration of remote sensing and ML for precision agriculture. Key findings highlight China's leadership and emerging AI themes, addressing gaps in thematic mapping and regional productivity. Future applications include policy frameworks for underrepresented regions and extensions to real-time monitoring systems, advancing food security and sustainability in the field.

Despite the valuable findings of this study, it is important to acknowledge some limitations. On one hand, there is the scope of the Scopus database, which, although one of the most comprehensive and high quality, excludes relevant publications from other sources.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Vladimir Henao-Cespedes	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

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 data that support the findings of this study are available from the corresponding author, APSC, upon reasonable request.

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