Assessing the advancement of artificial intelligence and drones' integration in agriculture through a bibliometric study

Hicham Slimani, Jamal El Mhamdi, Abdelilah Jilbab
Laboratory of Electronic Systems, Sensors and Nanobiotechnologies, ENSAM, Mohammed V University in Rabat, Rabat, Morocco

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ABSTRACT

Integrating artificial intelligence (AI) with drones has emerged as a promising paradigm for advancing agriculture. This bibliometric analysis investigates the current state of research in this transformative domain by comprehensively reviewing 234 pertinent articles from Scopus and Web of Science databases. The problem involves harnessing AI-driven drones' potential to address agricultural challenges effectively. To address this, we conducted a bibliometric review, looking at critical components, such as prominent journals, co-authorship patterns across countries, highly cited articles, and the co-citation network of keywords. Our findings underscore a growing interest in using AI-integrated drones to revolutionize various agricultural practices. Noteworthy applications include crop monitoring, precision agriculture, and environmental sensing, indicative of the field's transformative capacity. This pioneering bibliometric study presents a comprehensive synthesis of the dynamic research landscape, signifying the first extensive exploration of AI and drones in agriculture. The identified knowledge gaps point to future research opportunities, fostering the adoption and implementation of these technologies for sustainable farming practices and resource optimization. Our analysis provides essential insights for researchers and practitioners, laying the groundwork for steering agricultural advancements toward an enhanced efficiency and innovation era.

Corresponding Author:

Hicham Slimani
Laboratory of Electronic Systems, Sensors, and Nanobiotechnologies, ENSAM, Mohammed V University in Rabat
United Nations Avenue, Agdal, Rabat, Morocco
Email: hicham_slimani2@um5.ac.ma

1. INTRODUCTION

Drones are essential tools in agriculture because they are easy to use; they can get good images of their surroundings and acquire low-cost operations [1]. They are used in many agricultural remote sensing applications, like finding plant diseases [2], managing irrigation systems [3], and figuring out how much water the soil holds [4]. Cameras, multispectral sensors, and other remote sensing devices can also help drones get high-resolution images and collect data that can be used to find problem areas and develop many operational strategies. Drones are a cost-effective and efficient way to monitor crops and soil health, as they can scan large areas [5].

Artificial intelligence (AI) research and development [6] aims to develop a robot and system that mimic human intellect in language processing, image recognition [7], and decision-making. The primary capability of AI lies in its ability to automate complex operations [8], process enormous amounts of data [9], and enhance its performance incrementally. This capability presents a significant advantage for various fields, including agriculture [10], biomedicine [11], and business. However, it also invokes crucial ethical and practical considerations that must be addressed.

Farmers can now collect and analyze a vast amount of information concerning crop health, soil conditions, and weather patterns, allowing them to optimize their planting and harvesting techniques, increase yields, and decrease the utilization of water and fertilizers. Close monitoring of their fields is made possible by integrating drone technology and artificial intelligence (DAI) [12]. By analyzing drone data on various parameters, such as crop health, soil moisture, and nutrient deficiencies, AI detects potential risks, such as pests, diseases, and nutrient deficiencies, in real-time. This boosts agricultural output by enabling farmers to decide when to plant and harvest crops and when to use fertilizer and pesticides, depending on data [13]. Moreover, using drones and AI reduces labor costs and provides farmers with aerial photos and real-time information about crop growth, helping them make better-informed decisions. Integrating DAI in agriculture represents a significant step forward for the agricultural industry, offering farmers a more efficient and effective way to manage their crops. Farmers can better make good decisions by automating tasks and getting real-time data and images. This leads to higher yields and better crop management.

Pérez-Ortiz *et al.* [14] developed a system for weed mapping in precision agriculture in sunflower and corn fields using unmanned aerial vehicle (UAV) data. The approach uses machine learning and feature selection methods to increase precision and reduce user interaction. The results show that technology is suitable and promising for weed mapping in sunflower and corn crops. In [15], Ferreira *et al.* have devised a technique for weed detection and classification in soybean fields using convolutional neural networks (CNNs) using a Phantom DJI 3 Professional drone. CNNs were trained using the CaffeNet architecture, and Pynoviso was developed to categorize images using the learned model. Moreover, the results of CNNs were compared with those of other machine learning methods, such as support vector machines, AdaBoost, and random forests. In addition, Csillik *et al.* [16] proposed a technique for detecting and monitoring individual citrus and other crops. Romero *et al.* [17] used multispectral imaging and machine learning to figure out the stem water potential of grapevines. A model based on an artificial neural network (ANN) has demonstrated a strong correlation between grapevines estimated and actual water potential. A pattern recognition model for irrigation scheduling was constructed, as well. In [18], multispectral UAV aerial imagery monitors wheat for yellow rust.

The study presented by Gao *et al.* [19] aimed to develop a machine-learning system to identify spray and non-spray locations for drone-based sprayers. A mutual subspace method (MSM) was used to create two classifiers based on drone images. This method can be integrated into an autonomous drone spraying system for real-time applications. Maimaitijiang *et al.* [20] have contended that combining data from multiple sensors can give reasonably accurate estimates of plant features and valuable information for high spatial precision in agriculture and assessing plant stress. In [21], a method was presented using a deep learning model and color information to detect disease symptoms on leaves of grapevines from uncrewed aerial vehicle (UAV) images. The best results were obtained using a combination of luminance, blue-luminance, and red-luminance (YUV) color space and the excess green minus excess red index (ExGR) vegetation index, with an accuracy exceeding 95.8%. To refine classification, use multispectral UAV imagery, a deep learning algorithm, and a simple linear iterative clustering (SLIC) algorithm.

Kedia *et al.* [22] described an integrated spectral-structural method for detecting invasive vegetation species using red, green, and blue (RGB) and multispectral images acquired by unmanned aerial systems (UAS). The results show that structural information increases the accuracy of categorization. The research [23] illustrated a technique for counting agave plants using UAV overhead data. The data was used to create an orthomosaic and train a CNN model to trust plants. In addition, an AI-driven drone system was developed by [24] for real-time detection of hogweed. In [25], Schreiber *et al.* proposed a system based on DAI-RGB images for wheat biomass estimation.

In recent years, agricultural research has witnessed a surge in publications exploring the potential of DAI technology. Notably, researchers have addressed diverse agricultural challenges using DAI-powered applications. For instance, studies have focused on tomato disease detection [26], [27], potato cultivation [28]–[30], wheat yield prediction [31], [32], corn leaf detection and counting [33], apple tree yield prediction [34], white leaf disease detection in sugarcane [35], stress detection in rice plants [36], and soil water content prediction [37]. These groundbreaking studies reveal a rising need for using DAI technology to transform numerous facets of agriculture. In particular, DAI technology has become an effective tool for streamlining resource usage, supporting sustainable practices, and automating and improving agricultural operations. This research demonstrates the ability to handle contemporary agriculture’s complex issues, including disease monitoring, yield prediction, and stress detection, by utilizing the capabilities of AI, machine learning, and the internet of things (IoT). Integrating DAI technology with agricultural methods opens up opportunities for boosting crop yields, resource allocation, and precision farming practices. This research makes significant advancements in AI-powered agriculture, advancing the sector toward a more technologically advanced and sustainable future. These results provide the foundation for more developments and creative uses of DAI technology, opening the door for seismic shifts in the farming industry as global agricultural demands increase.

The quick adoption of artificial intelligence and drone technologies in agriculture generated significant research interest. Even if this convergence has been the subject of several research, it is still vital to carefully investigate the scope and influence of AI-driven drones on agricultural breakthroughs. Despite the possible advantages, a deeper comprehension of the extent and importance of this disruptive technology in influencing farming methods and fostering sustainability within the sector is required. Conducting a thorough bibliometric study to fill this research deficit is crucial to use bibliometric methodologies to uncover relevant research trends, prolific authors, significant publications, and emerging knowledge clusters associated with AI-driven drones in agriculture. Investigating author partnerships and co-citation networks will also illuminate how this topic's scholarly community and ideas are related. This research offers a clear and in-depth analysis of the present status of AI-integrated drone research in agriculture through a thorough bibliometric investigation. The findings of this study will provide insightful information to stakeholders, policymakers, and the academic community, encouraging a better knowledge of how AI-driven drones may affect agricultural innovation, sustainability, and efficiency.

By conducting a bibliometric analysis of DAI publications in agriculture between 2013 and 2022, visualizing the publication network, finding popular topics and research frontiers, and outlining a future research agenda, this study aims to address these needs. We methodically aggregate DAI in agriculture literature from Scopus and Web of Science as search objects to find essential topics, evolving trends, frontier research areas, and connections to other disciplines. We then analyze this literature using the information visualization software tool VOSviewer. Our study generalizes current technologies' authors, institutions, nations, keywords, and disciplinary categories. It also illustrates the relationships between co-occurring keyword references. We suggest ways to focus our collective research efforts on using DAI in agriculture by summarizing the work recommended by the most often cited authors in the current literature. In this way, we can solve the following research questions: i) What are the most prominent journals in the field?; ii) which papers have received the highest number of citations?; iii) Who are the most productive authors in this area?; iv) How do different countries contribute to co-authorship in this field?; v) what is the trend of collaboration among authors from different countries?; vi) What is the frequency of co-occurrence among authors' keywords?; and vii) what is the significance of this pattern?

2. MATERIALS AND METHODS

This study offers a clear and practical solution-a rigorous bibliometric analysis-to the urgent need for a thorough grasp of the revolutionary potential of AI-driven drones in agriculture. By utilizing reliable bibliometric methodologies, this work intends to thoroughly review and synthesize the literature on drone applications in agriculture, including AI. Our approach begins with a thorough literature assessment to find relevant publications from credible sources like Scopus and Web of Science. Our bibliometric analysis will be built on these papers, allowing us to learn valuable information about essential research trends, prolific authors, significant publications, and developing knowledge clusters. In addition, our method considers author cooperation networks and co-citation analysis to show how this field's academic community and ideas are interrelated. By visualizing and analyzing these networks, we can identify recurrent research themes and the working partnerships advancing the development of AI-driven drones for agriculture.

Our research will offer valuable insights into the state of AI-integrated drone research in agriculture through this thorough bibliometric analysis. Our findings will help the academic community, decision-makers, and other stakeholders understand how AI-driven drones affect agricultural innovation, sustainability, and efficiency. We can thoroughly examine the developments and insights provided by AI-driven drones in agriculture thanks to our obvious answer of using meticulous bibliometric analysis. This research will assist in opening the door for informed decision-making, focused research efforts, and the optimization of AI technologies to meet the possibilities and difficulties in contemporary agriculture by offering a thorough and evidence-based understanding of the area.

2.1. Material collection

The data for our study came from the Web of Science (WoS) and Scopus core databases. The search formula was ["agriculture" OR "plant" OR "crop" OR "field"] AND ["drone" OR "UAV" OR "unmanned aerial vehicle"] AND ["artificial intelligence" OR "deep learning"] AND ["languages: (English) AND types: (article or review)," which yielded 984 SCOPUS results and 953 Web of Science core collection results between 2013 and 2022. So, we found a total of 1,937 research papers. Since our study was only on agricultural applications and DAI, we reviewed the database and removed all duplicate or mismatched articles by hand. Books, letters, editorials, and reviews were not included because they contradicted the purpose of our experiment. Since our study was a comprehensive review, conference papers were also excluded. After applying these exclusion criteria, 234 articles from both databases were selected for bibliometric analysis. Publication data included title, year, authors, source document, country, research institution, and authors' keywords as shown in Figure 1.

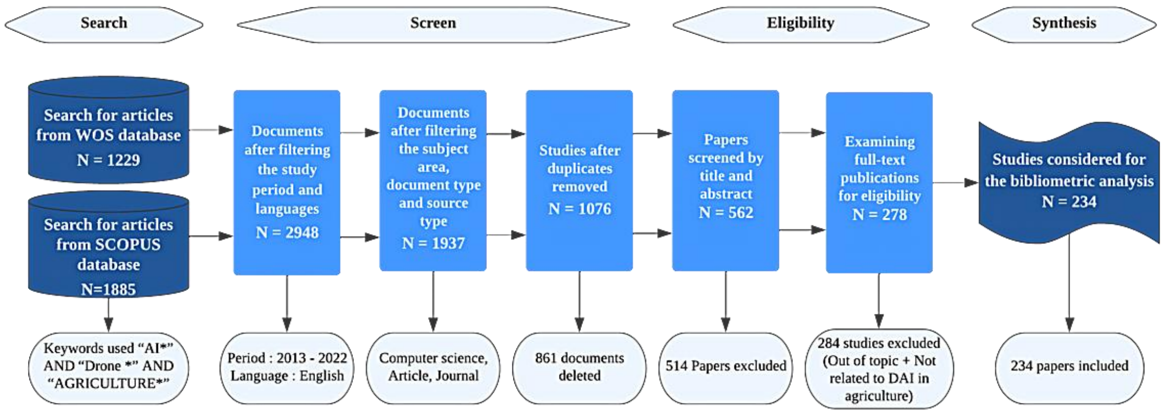

Figure 1. Research process

2.2. Data coding and analysis

A comprehensive analysis was conducted on the number of publications related to the field of agricultural DAI by using the Scopus and WoS databases. The data is presented in Figure 1, covering 2013 to 2022. The data was segmented into two distinct five-year intervals, 2013-2017 and 2018-2022, to provide a clear comparison. The results depicted in Figure 2 prove a marked variation in the number of DAI in agriculture publications across the two-time frames. While there were only nine publications in the earlier interval, the later break saw a significant increase with 225 publications. This finding suggests that there has been an exponential expansion of research in agricultural DAI over the past decade.

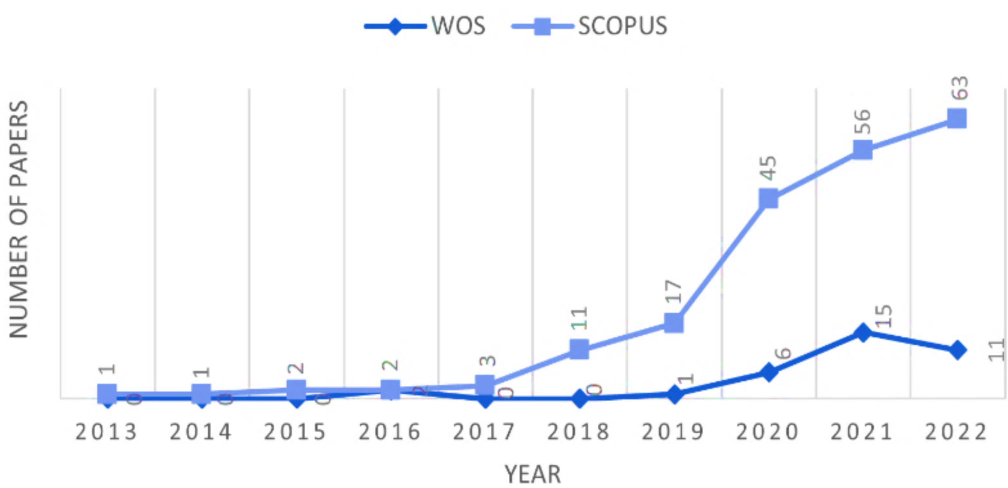

Figure 2. Agricultural DAI research papers published between 2013 and 2022

2.3. Tool and process

We extracted the necessary field data by deploying various algorithmic techniques after obtaining our two databases and plotting the scientific collaboration networks of countries and the disciplinary liaison networks; we also extracted keywords from the publications and created a map of co-citation clusters to perform hotspot analysis. We used VOSViewer software to show the growth of DAI in the field of agriculture. This was done by plotting and analyzing the data rules. In this seminal investigation, we employ bibliometric techniques as a reliable approach to address our research questions. Recognizing the inherent usefulness of bibliometrics is essential because it provides a distinct and quantitative perspective on the structural aspects of the field, which differs significantly from the traditional literature review technique. We gain unmatched insights into publication trends, co-citation networks, and authorial collaborations by meticulously applying bibliometric analysis to a large corpus of scholarly articles. This enables us to identify the complex dynamics of knowledge dissemination in our area of interest. On the other hand, traditional literature reviews tend to produce a qualitative synthesis of the existing literature, illuminating conceptual frameworks and thematic strands. By skillfully combining the benefits of bibliometric analysis and the traditional literature review, our study becomes a robust exegesis that resonates with thoroughness and academic rigor, augmenting our understanding of the subject and expanding the boundaries of intellectual inquiry.

3. RESULTS AND DISCUSSION

This extensive study’s descriptive analysis exposes several essential features of the research environment. First, it demonstrates the breadth and depth of scholarly contributions within the field. Second, it finds the best sources and most productive writers, providing insights into the essential books and writers advancing the area. The study also examines critical sources and widely cited books, offering insight into important texts influencing academic discourse. The crucial literature from 2018 to 2022 is also illuminated in this study, revealing the trends and advancements that occurred over this period. It clarifies word, author, and country co-authorship networks to improve our comprehension of scholarly cooperation, exposing the subtle linkages between academics and institutions. The research also reveals the citation networks, giving insight into the field's network of intellectual impact and information distribution. In summary, this study not only advances our understanding of the state of the field’s research but also sets the groundwork for its conceptual underpinnings. Our research aims to substantially contribute to this field’s academic knowledge and development using rigorous analysis.

3.1. Farming practices: a focus on relevant journals, highly cited papers, and DAI models

Table 1 shows the top ten journals by number of articles and citations. The journal “Computers and Electronics in Agriculture” is the only one with more than eighty articles. It is followed by the journal “Sensors” with nineteen publications and “Drone” with seventeen publications. No journals from agriculture or the environment are on the list. Instead, computer science and engineering journals assume most of the space.

Table 1. Top ten most relevant journals

Rank	Journal title	Number of articles	Number of citations
1	Computers And Electronics in Agriculture	85	1998
2	Sensors	19	130
3	Drones	17	242
4	Sensors (Switzerland)	16	303
5	ISPRS Journal of Photogrammetry and Remote Sensing	15	552
6	IEEE Access	14	354
7	Applied Sciences (Switzerland)	12	131
8	Ecological Informatics	7	99
9	IEEE Internet of Things Journal	5	131
10	Electronics (Switzerland)	5	16

In addition to the minimum citation threshold set at five, the VOSViewer software automatically displayed twelve sources that met the predefined criteria. The selection of this threshold ensures that only highly relevant and influential publications are included in our analysis, contributing to the robustness of our findings. These twelve sources represent a curated set of articles and publications that have garnered substantial attention and recognition within artificial intelligence and drone technology applied to agriculture.

The table above showcases the most cited journals in this specialized field, providing valuable insights into various publications’ scholarly impact and prominence. Notably, “Computers and Electronics in Agriculture” is the most frequently cited journal in 1998, signifying its significant contribution to advancing knowledge in this domain. Close behind is the “ISPRS Journal of Photogrammetry and Remote Sensing” with 552 citations, followed by “IEEE Access” with 354 citations, which have played pivotal roles in shaping the discourse surrounding AI and drone technology in agriculture.

To gain a deeper understanding of the influential research in this dynamic field, we further delve into the co-citation references of these top journals. Co-citation analysis allows us to identify shared connections between highly cited articles, providing insights into the interconnectedness of ideas and the collaborative relationships among researchers. The results of this analysis, visualized in Figure 3, offer a comprehensive representation of the intellectual landscape, revealing the key concepts and seminal works that have underpinned advancements in this interdisciplinary field.

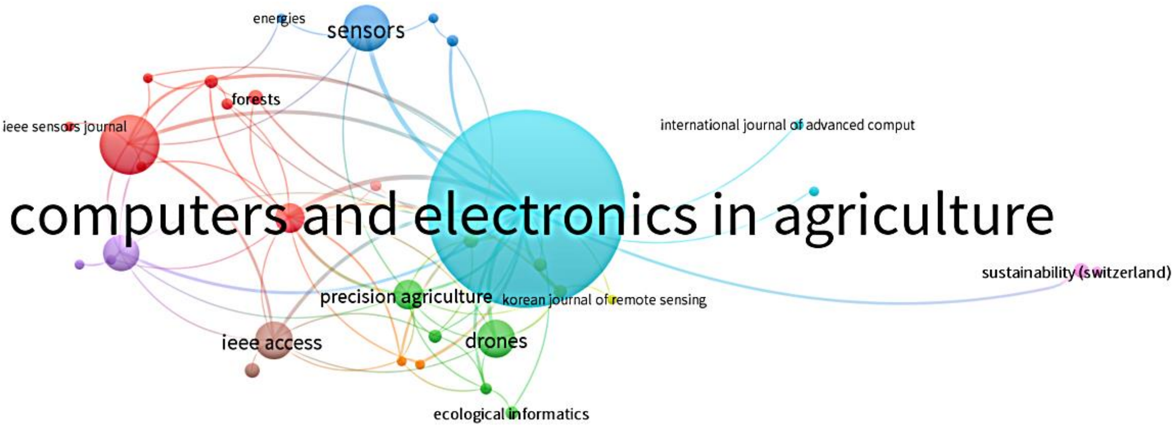

Figure 3. Co-citation references analysis of sources

To find the most critical research on using DAI in agriculture, we used citation analysis as part of our approach. We have then summarized the key results from these investigations. Table 2 provides a rating of the top 20 studies based on the total number of citations received to gauge the importance and impact of each research within the field. The publications by Ferreira *et al.* [15] and Maimaitijiang *et al.* [38] hold the top positions in citation count, with 247 and 181 citations, respectively. Following closely, Nevavuori *et al.* [39] accumulated a total of 175 citations.

Table 2. Top twenty most-cited papers on AI combined with drones for agriculture

Rank	Article reference	Year	Authors	Journal	Total of citations
1	[15]	2017	Ferreira *et al.*	Computers And Electronics in Agriculture	247
2	[38]	2017	Maimaitijiang *et al.*	ISPRS Journal of Photogrammetry and Remote Sensing	181
3	[39]	2019	Nevavuori *et al.*	Computers And Electronics in Agriculture	175
4	[40]	2020	Gupta *et al.*	IEEE Access	165
5	[41]	2018	Kerkech *et al.*	Computers And Electronics in Agriculture	132
6	[16]	2018	Csillik *et al.*	Drones	129
7	[18]	2018	Su *et al.*	Computers And Electronics in Agriculture	124
8	[42]	2015	Pérez-Ortiz *et al.*	Applied Soft Computing Journal	119
9	[17]	2018	Romero *et al.*	Computers And Electronics in Agriculture	114
10	[14]	2016	Pérez-Ortiz *et al.*	Expert Systems with Applications	113
11	[43]	2020	Osco *et al.*	ISPRS Journal of Photogrammetry and Remote Sensing	88
12	[21]	2020	Kerkech *et al.*	Computers And Electronics in Agriculture	81
13	[44]	2020	Ramos *et al.*	Computers And Electronics in Agriculture	73
14	[45]	2020	Ampatzidis *et al.*	Computers And Electronics in Agriculture	66
15	[46]	2020	Tetila *et al.*	Computers And Electronics in Agriculture	65
16	[47]	2021	Kumar *et al.*	Computer Networks	60
17	[48]	2019	Kwak and Park	Applied Sciences (Switzerland)	56
18	[49]	2020	Gašparović *et al.*	Computers And Electronics in Agriculture	55
19	[50]	2019	Ampatzidis *et al.*	Computers And Electronics in Agriculture	55
20	[51]	2021	Jia *et al.*	Environmental Pollution	51

The recent global trend of DAI adoption in the agricultural arena is depicted in Figure 4. To fully utilize the potential of this technology, a wide range of cultural activities from various geographical locations have included different artificial intelligence models, machine learning, and deep learning. The results show that these technological developments significantly influence the price of cultural events, with noticeable rises established in 2018 and 2022. This data-driven research demonstrates how DAI has significantly changed agriculture practices worldwide. Stakeholders in the cultural sector have started a revolutionary path by integrating artificial intelligence-driven models into drones, increasing productivity, accuracy, and sustainability. Drone technology combined with artificial intelligence, machine learning, and deep learning algorithms has advanced agricultural operations to new levels and encouraged creative solutions to pressing problems. The apparent increase in DAI use throughout the examined time denotes a paradigm shift in the environment of cultural activities. The growing use of advanced DAI technology is a purposeful reaction to the changing needs of a rapidly changing world. Such initiatives have significantly affected the cultural industry, ushering in a time of data-driven decision-making and efficient resource use. Figure 4 provides a graphic illustration of technology's significant contribution to agriculture. This study provides valuable insights into the transformational potential of DAI on a worldwide scale as the field of cultural activities continues to embrace and adjust to the possibilities made possible by DAI and its associated paradigms.

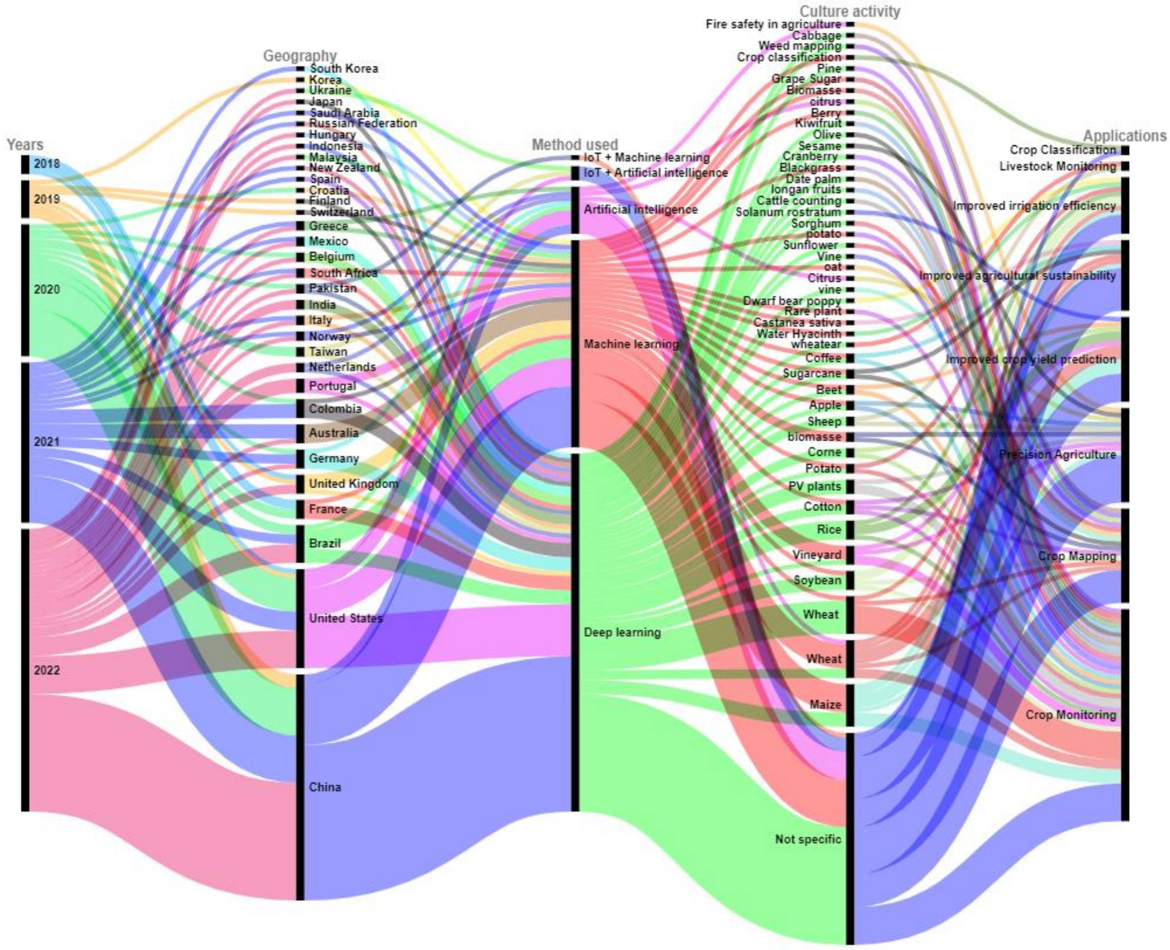

Figure 4. Farming activities and DAI agricultural models were recently used

Figure 5 presents the results of a co-citation analysis and clustering, conducted with a minimum citation threshold of twenty, to elucidate the interrelationships between publications in the DAI field. The study reveals compelling insights into this domain's scholarly connections and knowledge dissemination. The findings of the co-citation analysis highlight notable authors whose work resonates significantly with the DAI research. Among the relevant publications, Girshick, R appears as the most frequently co-cited author, garnering 77 citations, followed closely by He, K with 70 citations, and Zhang, X with 69 citations. These results underscore the substantial impact of their research contributions and their crucial role in shaping the landscape of DAI research. This evidence suggests that the works of Girshick, R, He, K, and Zhang, X hold significant academic influence and are regarded as pivotal references by their peers. By discerning the core contributors and influential publications through the co-citation analysis, our study contributed to the holistic understanding of the network of ideas and thought leaders in agricultural DAI research.

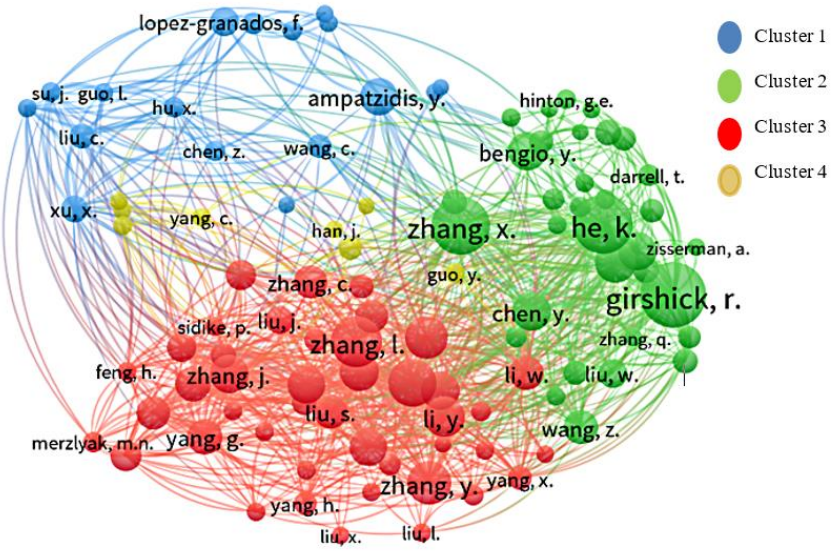

Figure 5. Leading cited researchers (a co-citation and clustering analysis)

3.2. Country co-authorship analysis

As depicted in Figure 6, our data reveals that the top ten publishing nations are China, the United States (US), India, Saudi Arabia, Brazil, Australia, the United Kingdom (UK), South Korea, Italy, and Pakistan. The top three nations alone account for 51.50% of all publications. Notably, China and the United States published more than 35 papers each, with China accounting for 20.70% and the US for 16.87% of the total publications, significantly surpassing the combined total of the remaining eight nations.

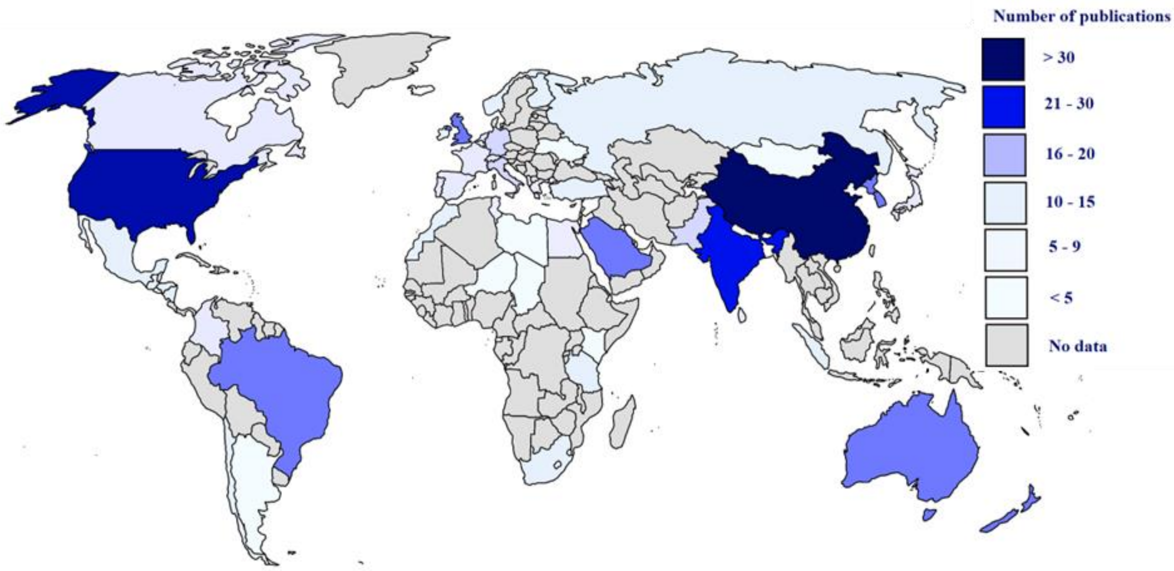

Figure 6. Global geographical distribution of publications from 2018 to 2022: A numerical analysis

The network of collaboration among nations from 2018 to 2022 is presented in Figure 7. The analysis shows that China and the United Kingdom have produced the highest number of collaborative papers with numerous countries, including Brazil, Australia, France, and India. The analysis of interdependence centrality reveals that the United States, China, and Saudi Arabia are the vital connecting nations in the collaboration network. The interdependence centrality metric assesses the frequency with which a particular node is found on the shortest path between two other nodes in the network.

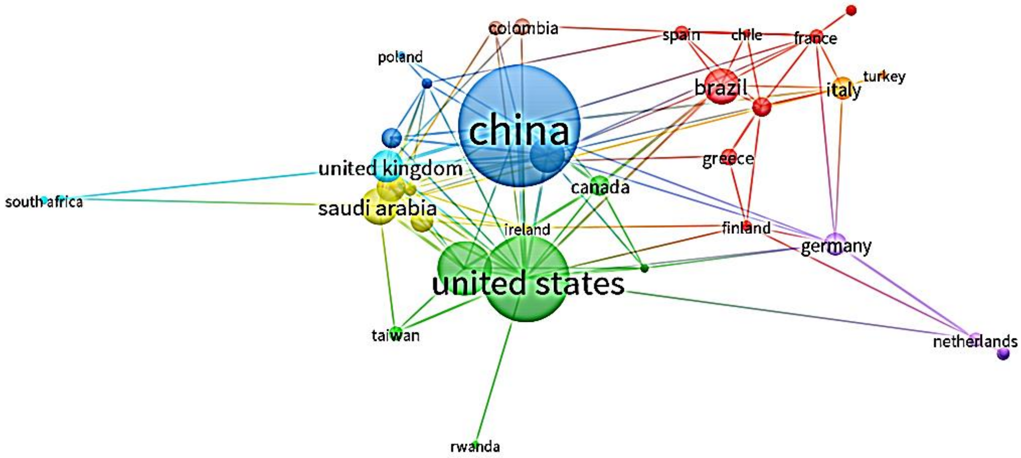

Figure 7. Collaboration network of countries

3.3. Co-occurring authors' keywords

The keyword density map generated by the VOSviewer software, depicted in Figure 8, employs the use of color and font size to indicate the frequency of keywords found in DAI-related agriculture publications. The frequency of keywords increases as the font size enlarges and the shade of yellow becomes lighter. A total of 65 keywords were identified and grouped into five categories based on a minimum of three occurrences for each keyword. The largest group comprised 14 keywords. The most frequently used keywords, showcasing a noteworthy density, are unmanned aerial vehicle (22.38%), followed by deep learning (15.88%), machine learning (9.92%), precision agriculture (8.30%), and remote sensing (5.95%). These keywords hold significant relevance to research in DAI technology in agriculture. They are closely linked to keywords such as "smart agriculture," "artificial intelligence," "IoT," "image classification," and "transfer learning."

The top ten most frequently occurring keywords for each cluster are depicted in Table 3. This table comprehensively overviews each cluster's most commonly used keywords. This information is presented to help the reader understand the main themes and topics discussed within each cluster. Showing the most frequently used keywords allows quick and easy identification of the discussed issues. It helps to give a clearer understanding of the content within each cluster.

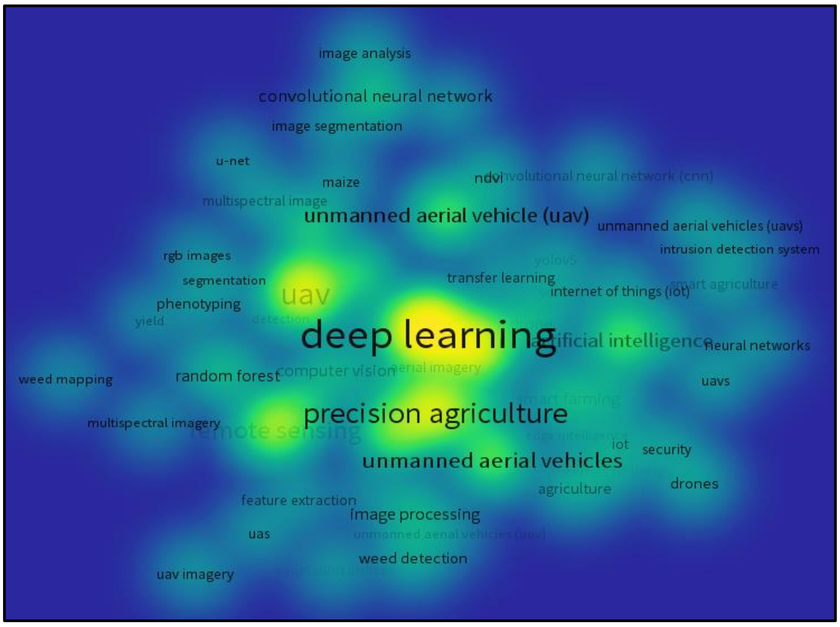

Figure 8. Visualization of keywords density

Table 3. Most frequent keywords in each cluster

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Deep neural networks	Agriculture	Aerial imagery	CNN	Artificial intelligence
UAV	Artificial intelligence	ANN	Features extraction	CNN
Image analysis	Drones	Multispectral imagery	Image processing	Intrusion detection
Image segmentation	Edge computing	Random forest	Precision agriculture	Neural networks
Machine learning	Edge intelligence	Remote sensing	UAS	Smart agriculture
CNN	Internet of things	SVM	UAVs	UAVs
Transfer learning	Security	UAV	Vegetation indices	-
NDVI	Smart farming	Weed detection	-	-
Multispectral	Precision agriculture	-	-	-
Classification	-	-	-	-

Implementing artificial intelligence with drones (DAI) might improve the monitoring of agricultural activities. Drones can perform various tasks, including picture capture, field mapping, and detecting farming pests, illnesses, and water stress. Our qualitative assessment and bibliometric evaluation findings provide insightful information for researchers looking at DAI in agriculture and point to possible directions for further investigation. Despite the growing body of research, an assessment of forthcoming advancements in DAI and agricultural uses is still necessary. By addressing the critical issues and areas of research at the nexus of DAI and agriculture, this study seeks to close this knowledge gap.

Our research has discovered a significant increase in articles exploring the use of DAI in agriculture between 2018 and 2022. The leading journals contributing to the body of knowledge in this field are "Computers and Electronics in Agriculture," "Journal of Photogrammetry and Remote Sensing," and "IEEE Access." Although the United States boasts the highest citation count, Asian nations have demonstrated greater overall productivity. Our study offers insightful perspectives on the potential impact of DAI in agriculture. Our examination of the most frequently cited publications highlights the central role of precision agriculture in AI applications aimed at enhancing agricultural efficiency and sustainability. Our keyword cluster analysis of DAI in agriculture studies reveals several clusters, including "Artificial intelligence-based learning systems for agriculture," "Internet of Things and drones for agriculture," and "Plant disease detection using drones and artificial intelligence." Many of the experiments employ advanced AI techniques, such as deep learning, attracting significant interest due to their ability to improve farmers' understanding of agricultural conditions.

This study highlights the urgent need for further research into how DAI can influence agricultural fields and promote sustainability within agricultural supply chains. The use of DAI by the farming industry has significant ramifications that require in-depth and ongoing research. Further research into DAI's many impacts and benefits is essential to improve understanding of its potential implications for agriculture. This experimental mindset is critical for discovering state-of-the-art strategies and techniques to exploit DAI's revolutionary potential fully. This study highlights the dynamic and changing nature of the agricultural environment under the influence of DAI, underlining the need for ongoing research. To fully utilize the enormous potential of DAI to transform and improve agriculture, continued research efforts are essential.

4. CONCLUSION

This study analyzed publications about using artificial intelligence and drones (DAI) in agriculture using bibliometric analysis and a network visualization technique. According to our research, there has been an increase in publications on DAI in agriculture, especially between 2018 and 2022. Notably, publications from China and the United States exceeded those from other nations by a large margin, with China dominating in total publications and being the only nation with more than 80 articles. Conversely, the United States had the most citations around DAI in agriculture. This field was also known for being multidisciplinary. It included subjects like "Agriculture," "Computer Science," "Environmental Science and Ecology," and "Engineering and Electrical," with "Computer Science" being the most closely related. Despite progress, the development of DAI in agriculture may need more international collaboration. According to our study, the development of DAI in agriculture started with looking at images taken by drones directly, moved on to minor improvements in image processing, and ended with the development of machine learning methods like neural networks for image segmentation. We suggest topics for further study based on our results, including data sources, modeling approaches, applications, and technology. Additionally, we recommend that more research be done using artificial intelligence and deep learning techniques to address problems relating to various crops, such as plant disease detection, irrigation and fertilization system management, environmental sustainability, and crop yield improvement. The findings of this study provide the scientific community with a helpful starting point for comprehending DAI developments in agriculture.

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BIOGRAPHIES OF AUTHORS

Hicham Slimani received a research master’s in electrical engineering from “École Nationale Superieur des Arts et Métiers’’ (ENSAM Ex-ENSET), Mohammed V University, Rabat, Morocco. He is a Ph.D. student in the “Electronic Systems, Sensors and Nanobiotechnologies” laboratory research team of ENSAM/ENSIAS. His research interests include IoT, artificial intelligence and data communication, and wireless sensor networks. He can be contacted at email: hicham_slimani2@um5.ac.ma.

Jamal El Mhamdi is a professor of electrical engineering at "École Nationale Superieur des Arts et Métiers'' (ENSAM, Ex-ENSET), Mohammed V University, Rabat, Morocco. He acquired a Ph.D. in electrical, electronic, and telecommunication engineering from the University of Rennes, France, in 1988. His research interests lie in the fields of signal processing, communication systems, and artificial intelligence. He can be contacted at email: j.elmhamdi@um5r.ac.ma.

Abdelilah Jilbab is a professor of electrical engineering at "École Nationale Superieur des Arts et Métiers'' (ENSAM, Ex-ENSET), Mohammed V University, Rabat, Morocco. He acquired a Ph.D. in Computer and Telecommunication from Mohammed V-Agdal University, Rabat, Morocco, in February 2009. His thesis concerns the filtering of illegal sites on the internet: contribution to the type of image recognition based on the principle of maximum entropy. His research interests focus on image processing, engineering, information systems, and artificial intelligence. He can be contacted at email: Abdelilah.jilbab@ensam.um5.ac.ma.