REVIEW ARTICLE Indian Journal of Agricultural Research, Volume 60 Issue 5: 635-646 (May 2026)

Smart Farming and Digital Agriculture: A Bibliometric Perspective on Past, Present and Future Research Trends

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10.18805/IJARe.AF-1023

ABSTRACT

The intersection of agriculture and technology is increasingly vital in addressing global challenges such as food security, climate change and sustainable productivity. Understanding the evolution of this field provides insights into research priorities and innovation pathways. This bibliometric review analyzes peer-reviewed literature from the Scopus database to map developments at the agriculture-technology nexus. Citation, co-citation and co-word analyses were used to identify influential publications, intellectual structures and thematic trends. The study focused on country-level contributions, keyword clusters and foundational literature. Contributors to the field include China, the United States and India. Research is notably clustered around topics such as remote sensing, climate-smart agriculture and decision support systems. Co-citation analysis highlighted foundational studies that shape the intellectual core, while co-word analysis identified emerging themes like smart farming, sustainability and automation. Limitations of the study include language and database bias, exclusion of non-indexed works and overreliance on citation metrics. Additionally, high costs and infrastructural challenges limit the adoption of advanced technologies in developing regions. The study advocates for integrating qualitative methods and expanding data sources in future bibliometric research. Strategic insights are offered to support researchers, practitioners and policymakers navigating the digital transformation of agriculture.

Key words: Agriculture, Bibliometric analysis, Science mapping, Smart agriculture, Sustainable development goals, Technology.

Recent advances in digital agriculture have intensified the integration of artificial intelligence (AI), the Internet of Things (IoT), remote sensing and precision agriculture to enhance productivity, sustainability and food security. In parallel, bibliometric analysis has become an important tool for synthesizing large bodies of literature, identifying research trends and revealing knowledge structures within rapidly evolving fields. A growing number of studies report a sharp increase in publications on AI and Industry 4.0 technologies in agriculture, particularly since 2018, with China, the United States and India leading global research output (Bhagat *et al*., 2022). Technologies such as IoT, unmanned aerial vehicles, blockchain, drones, sensors and GPS-based systems have been widely examined, revealing dominant thematic clusters and strong potential for improving resource-use efficiency and decision-making (Fasciolo *et al*., 2024; Guamán-Rivera, 2023). At the same time, empirical and bibliometric studies highlight persistent adoption constraints related to high costs, infrastructure limitations and shortages of technical expertise (Charania and Li, 2020; Guamán-Rivera, 2023).

Recent research also demonstrates the practical impact of digital tools on agricultural management. Mobile applications such as Crop Doctor 2.0 support timely disease diagnosis and farm-level decision-making (Bhardwaj and Saxena, 2024), while automated irrigation systems, biotechnology, nanotechnology and real-time monitoring platforms have contributed to yield improvement and environmental sustainability (Modjo *et al*., 2024; Gawande *et al*., 2023). Scoping reviews further indicate that multimedia-based technologies remain dominant in agricultural extension, although their effectiveness varies across contexts (Xu *et al*., 2023). Studies on global agricultural trade and innovation additionally show uneven research coverage across periods and regions, with China emerging as a major contributor in recent years (Rathee, 2023).

Bibliometric analyses have increasingly been used to examine smart farming, agricultural innovation and entrepreneurship. For example, research on IoT-enabled agriculture has identified key authors, collaboration networks and thematic structures (Iqbal *et al*., 2022; Singh *et al*., 2020), while studies on agricultural innovation emphasize trends such as robotic farming, biotechnology, supply chain management and green practices (Wahyudi and Kiminami, 2021; Shen *et al*., 2022). Despite these contributions, existing bibliometric studies are often technology-specific or regionally focused and provide limited integrated cluster-level interpretation. Moreover, crop-specific perspectives, particularly rice-based systems that are central to global food security, remain underexplored.

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How to cite this article: Pulumbarit, J.P. (2026). Smart Farming and Digital Agriculture: A Bibliometric Perspective on Past, Present and Future Research Trends. *Indian Journal of Agricultural Research*. **60(5):** 635-646. doi: 10.18805/IJARe.AF-1023.

Submitted: 12-01-2026 **Accepted:** 12-03-2026 **Online:** 24-04-2026

To address these gaps, this study presents a comprehensive bibliometric review of agriculture and digital technology research using Scopus data. By integrating citation, co-citation and co-word analyses, the study offers a structured interpretation of thematic clusters, highlights rice-centric research patterns and proposes a future research agenda. Specifically, the objectives are to: (i) identify influential publications through citation analysis; (ii) examine the intellectual structure of the field using co-citation analysis and (iii) explore emerging and future research themes through co-word analysis.

Bibliometric analysis

This study adopts a bibliometric approach, a quantitative method used to systematically analyze academic literature in order to identify patterns, relationships and intellectual structures within a research domain (Donthu *et al*., 2021; Passas, 2024). Bibliometric analysis supports science mapping by visualizing thematic trends, influential contributions and conceptual linkages using bibliographic metadata (Zupic and Èater, 2014). The standard workflow comprises six stages: research design, data collection, search refinement, bibliometric analysis, qualitative interpretation and result reporting (Moresi *et al*., 2021). Compared with systematic literature reviews and meta-analyses, bibliometric methods reduce subjectivity and enable the analysis of large-scale scholarly datasets. Advances in network analysis and text mining have further enhanced the analytical depth of science mapping techniques (Chen *et al*., 2023). This study applies three complementary bibliometric techniques: citation analysis, co-citation analysis and co-word analysis, to comprehensively examine the evolution, structure and emerging themes of agriculture-technology research.

Citation analysis

Citation analysis is employed to identify influential publications, authors, institutions and countries by examining citation frequencies (Martins *et al*., 2022). It provides insights into scholarly impact, knowledge diffusion and research leadership across disciplines (Arencibia-Jorge *et al*., 2020). Citation indicators also reflect collaboration patterns and geographic research concentration (Roy and Basak, 2013). To reduce bias, self-citations were not emphasized in interpretive analysis, acknowledging known limitations of citation-based metrics (Osareh, 1996; Kim and AlZubi, 2024).

Co-citation analysis

Co-citation analysis examines the intellectual structure of a field by measuring how frequently pairs of documents are cited together. Frequently co-cited documents are assumed to share conceptual or theoretical similarity, thereby revealing foundational works and dominant research schools (Noma, 1984; Trujillo and Long, 2018). Similarity measures such as Salton's cosine and Jaccard's index were used to strengthen network reliability and cluster formation (Grácio and de Oliveira, 2013).

Co-word analysis

Co-word analysis explores the thematic structure of the literature by examining keyword frequency and co-occurrence patterns (Coulter *et al*., 1998; Delecroix and Eppstein, 2004; Armenta-Medina *et al*., 2020). This method enables the identification of core themes, emerging topics and conceptual evolution over time. Strategic thematic mapping was applied to support research forecasting and trend interpretation, consistent with prior bibliometric applications (Khasseh *et al*., 2021).

Research design and data collection procedures

Data were retrieved from the Scopus database, one of the most comprehensive and curated citation and abstract sources covering peer-reviewed journals across scientific disciplines (Baas *et al*., 2020). Scopus currently indexes over 90 million records from more than 25,000 active titles and is widely used in bibliometric research due to its broad coverage and consistent quality control (Zhu and Liu, 2020; Niknejad *et al*., 2021). The analysis was limited to peer-reviewed journal articles published between 2019 and 2024, ensuring academic rigor and temporal consistency. Books, book chapters and conference proceedings were excluded to maintain comparability and citation reliability (Mingers *et al*., 2012; Cho *et al*., 2024; AlZubi and Al-Zu'bi, 2023). The final dataset consisted of 3,219 documents after data cleaning, which involved removing duplicates, incomplete records and non-relevant studies based on title, abstract and keyword screening. Bibliometric analyses were performed using VOSviewer and the Bibliometrix package in R, which are well-suited for network visualization, cluster detection and thematic evolution analysis. The complete methodological workflow from data retrieval to analysis and visualization is shown in Fig 1.

The search strategy combined agriculture-, technology- and crop-specific keywords, as summarised in Table 1. Importantly, rice-related keywords were included to enable crop-specific thematic analysis within the broader agriculture-technology domain. Rice is one of the world's most critical staple crops and a major focus of digital agriculture innovation, particularly in Asia. Including rice-specific terms allows this study to capture both general smart farming trends and crop-centric research dynamics, thereby addressing an underexplored dimension in existing bibliometric reviews.

Threshold values were applied to improve analytical clarity and network interpretability. A minimum citation threshold (≥8 citations) was used in citation and co-citation analyses to filter out marginally cited documents and focus on influential literature. Similarly, a keyword occurrence threshold (≥75 occurrences) was selected in co-word analysis to retain high-frequency, thematically significant terms while reducing noise. These thresholds are consistent with prior large-scale bibliometric studies and were determined iteratively to balance network density and interpretability. Fig 2 presents the annual number of publications and citations related to agriculture and technology, illustrating a steady growth in research output over time.

Citation analysis

Citation analysis identified the most influential publications in agriculture and technology research. Table 2 lists the top 10 highest-cited documents. The three most cited studies are Thenmozhi *et al*. (2019) with 578 citations, Wang *et al*. (2021) with 368 citations and Basso *et al*. (2018) with 388 citations, indicating their strong academic impact.

Overall, the highly cited publications predominantly focus on deep learning for crop disease detection, remote sensing and hyperspectral analysis and digital decision-support systems for yield forecasting. These studies highlight the central role of artificial intelligence, big data and sensing technologies in precision agriculture and sustainable crop management.

Co-citation analysis

Co-word analysis was conducted using author keywords and index terms. Out of 3,219 documents, 47 publications met the minimum citation threshold of eight, forming a co-citation network comprising four distinct clusters. The most influential references based on total link strength were Gorelick *et al*. (2017); Mosleh *et al*. (2015) and Breiman (2001), indicating their foundational role in agriculture-technology research. Table 3 presents the top 10 documents with the highest co-citation frequency and total link strength.

Fig 3 illustrates the co-citation network, where clusters are clearly differentiated, reflecting distinct intellectual foundations within the field. Cluster labels were assigned through inductive interpretation of representative publications and shared thematic orientations.

Cluster 1 (Red)

Innovations in Water Management and the Diffusion of Agricultural Technologies. This cluster centers on the integration of water management practices, technological innovation and adoption behavior in agriculture, particularly in the context of rice production and sustainability. A prominent theme is the need to optimize irrigation techniques under increasing water scarcity. Key studies such as Bouman *et al*. (2007) and Carrijo *et al*. (2017) highlight alternate wetting and drying (AWD) as a promising irrigation method that conserves water without compromising rice yields. These insights are further supported by Dong *et al*. (2016) and Lampayan *et al*. (2015), who provide evidence on the economic viability and farmer adoption of AWD in irrigated lowland rice systems. In a broader context, the seminal work of Evenson and Gollin (2003) on the Green Revolution provides historical grounding by assessing how technological advancements have shaped agricultural productivity across decades. This aligns with Godfray *et al*. (2010) and Su *et al*. (2023), who underscore the global challenge of ensuring food security for a growing population, calling for innovations in both policy and practice. Kassie *et al*. (2015) explored the adoption of sustainable intensification practices in African regions, revealing socio-economic and environmental factors influencing uptake. Altogether, this cluster underscores the critical intersection of water management, innovation adoption and sustainable intensification as essential strategies to address global agricultural and environmental challenges.

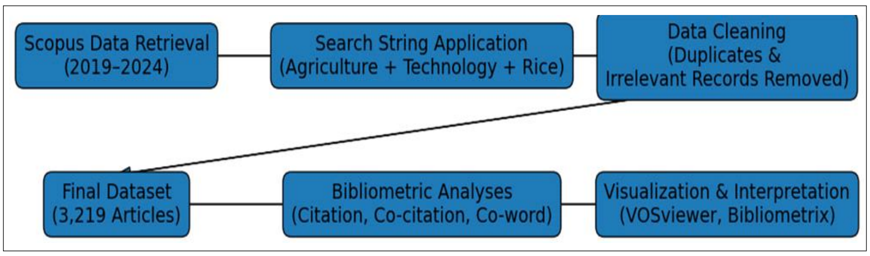

Fig 1: Methodological workflow for bibliometric analysis.

Table 1: Search string in scopus database.

Key words	Justification
("Agriculture" OR "farming" OR "crop production" OR "agricultural sector" OR "precision agriculture" OR "smart farming")	To identify literature related to agriculture
("Technology" OR "digital technology" OR "emerging technology" OR "agricultural innovation" OR "automation" OR "ICT" OR "AI" OR "remote sensing" OR "drones" OR "Internet of things")	To identify literature related to technology
("Rice" OR "rice farming" OR "rice production" OR "paddy fields")	To capture crop-specific digital agriculture research, with a focus on rice-based production systems

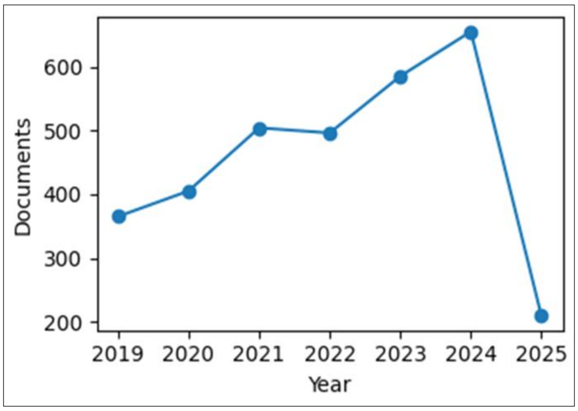

Fig 2: Number of publications and citations on agriculture and technology (Source: Scopus).

Cluster 2 (Green)

Remote Sensing and Machine Learning for Precision Agriculture and Crop Yield Prediction*.* This cluster highlights the convergence of remote sensing technologies, vegetation indices and machine learning techniques in advancing precision agriculture, particularly in rice and soybean yield prediction. Foundational works by Huete *et al*. (2002) and Gitelson *et al*. (2003) laid the groundwork for vegetation index development (*e.g.*, SAVI, NDVI) and chlorophyll estimation, which remain vital for crop monitoring. These indices help assess plant health, biomass and productivity from satellite and UAV imagery. Recent studies demonstrate how these indices integrate with cutting-edge platforms like Google Earth Engine (Gorelick *et al*., 2017), enabling scalable geospatial analyses. Mosleh *et al*. (2015) exemplify the application of

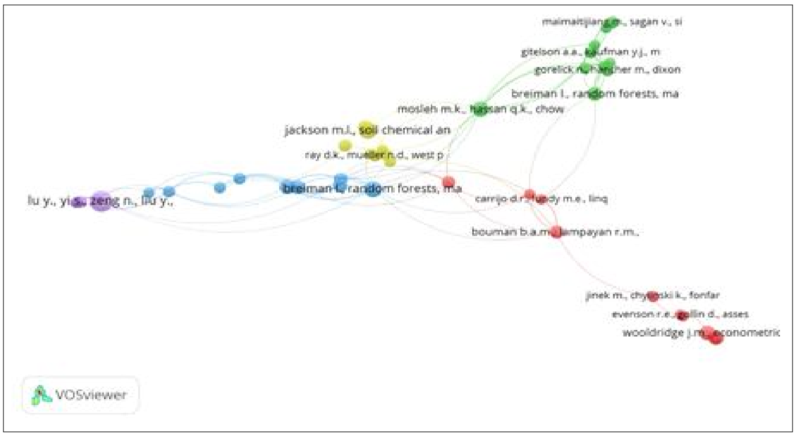

Fig 3: Co-citation analysis of agriculture and technology.

Table 2: Top 10 highest-cited documents.

Authors	Title	Citations
Thenmozhi *et al*. (2019)	Crop pest classification based on deep convolutional neural network and transfer learning	578
Wang *et al*. (2021)	A review of deep learning used in hyperspectral image analysis for agriculture	368
Basso *et al*. (2018)	Seasonal crop yield forecast: Methods, applications and accuracies	388
Thomas *et al*. (2021)	Intelligent agricultural machinery using deep learning	205
Belaud *et al*. (2019)	Big data for agri-food 4.0: Application to sustainability management for by-products supply chain	205
Oladele *et al*. (2019)	Influence of rice husk biochar and inorganic fertilizer on soil nutrients availability and rain-fed rice yield in two contrasting soils	203
Upadhyay *et al*. (2022)	Root exudates: mechanistic insight of plant growth promoting rhizobacteria for sustainable crop production	183
Srivastav *et al*. (2021)	Climate-resilient strategies for sustainable management of water resources and agriculture	169
Chen *et al*. (2020)	Electronic agriculture, blockchain and digital agricultural democratization: Origin, theory and application	161
Habib-Ur-Rahman (2022)	Impact of climate change on agricultural production; Issues, challenges and opportunities in Asia	159

MODIS time-series imagery for mapping rice paddies and predicting yields, while Maimaitijiang *et al*. (2020) demonstrated the shift toward UAV-based monitoring and deep learning models for yield estimation at fine spatial resolutions. Machine learning, particularly Random Forests (Breiman, 2001), plays a crucial role in handling high-dimensional remote sensing data, enabling accurate predictions and classifications across diverse agroecological settings. The fusion of multi-temporal, multispectral and RGB data has significantly enhanced model precision and transferability, especially in smallholder farming systems. Collectively, this cluster reflects a technological shift in agriculture-from manual monitoring to data-driven, sensor-based systems-supporting real-time decision-making, sustainable resource management and increased productivity through agricultural intelligence.

Cluster 3 (Blue)

Deep Learning and Remote Sensing Synergy for Advanced Agricultural Monitoring. This cluster reflects the evolving intersection of deep learning and remote sensing technologies in modern agriculture, emphasizing methods that transform how agricultural landscapes, particularly rice paddies, are monitored and analyzed at scale. Foundational studies like Tucker (1979) and Weiss *et al*. (2020) highlight the historical and meta-analytical evolution of remote sensing applications, particularly in vegetation monitoring and agricultural assessment. Breiman's (2001) seminal work on Random Forests laid a critical statistical foundation for non-linear, high-dimensional modeling, enabling agricultural researchers to better process satellite data and yield predictions. The relevance of machine learning and deep learning models becomes even more evident through contributions from LeCun *et al*. (2015); Simonyan and Zisserman (2014) and He *et al*. (2016), who developed the CNN and ResNet architectures widely used in agricultural image classification and object detection tasks. Dong and Xiao (2016) provide a systematic review of paddy rice mapping techniques, illustrating a shift from localized to global-scale approaches. Complementing this, the

Table 3: Top 10 documents with the highest in co-citation and total link strength.

Rank	Publication	Citation	Total link strength
1	Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D. and Moore, R. (2017). Google earth engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. **202:** 18-27.	12737	17
2	Mosleh, M.K., Hassan, Q.K. and Chowdhury, E.H. (2015). Application of remote sensors in mapping rice area and forecasting its production: A review. *Sensors.* **15(1):** 769-791.	363	17
3	Breiman, L. (2001). Random forests. *Machine Learning.* **45:** 5-32. https://doi.org/10.1023/A:1010933404324.	151237	16
4	Dong, J., Xiao, X., Menarguez, M.A., Zhang, G., Qin, Y., Thau, D., Biradar, C. and Moore, B. (2016). Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and google earth engine. *Remote Sensing of Environment.* **185:** 142-154. https://doi.org/10.1016/j.rse.2016.02.016.	818	15
5	Gitelson, A.A., Kaufman, Y.J. and Merzlyak, M.N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment.* **58(3):** 289-298.	3598	15
6	Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X. and Ferreira, L.G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*. **83(1-2):** 195-213.	10740	15
7	Lu, Y., Yi, S., Zeng, N., Liu, Y. and Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. *Neurocomputing.* **267:** 378-384.	1128	14
8	Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment.* **8(2):** 127-150.	13699	14
9	Su, X., Wang, J., Ding, L., Lu, J., Zhang, J., Yao, X., Cheng, T., Zhu, Y., Cao, W. and Tian, Y. (2023). Grain yield prediction using multi-temporal UAV-based multispectral vegetation indices and endmember abundance in rice. *Field Crops Research.* **299:** 108992. https://doi.org/10.1016/j.fcr.2023.108992.	29	13
10	Weiss, M., Jacob, F. and Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment*. **236:** 111402.	1620	13

Google Earth Engine platform (Gorelick *et al*., 2017) enables large-scale geospatial analyses and democratizes access to planetary-scale agricultural data, facilitating scalable machine learning integration in crop monitoring. This cluster signifies a broader trend: the integration of AI-driven analytics with remote sensing to automate and refine agricultural insights. These technologies support precision farming, yield forecasting and resource optimization, positioning agriculture as a data-rich domain poised for transformative innovation.

Cluster 4 (Yellow)

Global Agricultural Sustainability and Food Security in the Face of Climate Challenges. This cluster highlights pivotal contributions to understanding the global sustainability of agricultural systems, emphasizing food security, climate change and the intensification of crop production. Chauhan *et al*. (2017) offer a comprehensive global perspective on rice production, a staple for billions, underscoring the pressures faced by this critical crop under environmental and socio-economic constraints. Foley *et al*. (2011) explored the planetary boundaries of agriculture, arguing that current yield trends are inadequate to meet future food demands, especially by 2050. These concerns are echoed by Wheeler and von Braun (2013), who underscore the impact of climate change on global food security, calling for urgent adaptation and mitigation strategies in food systems. Classic works by Gomez and Gomez (1984) and Jackson (1973) reinforce the importance of robust statistical and soil analysis methods, which continue to underpin modern agronomic research. Their inclusion reflects the enduring relevance of rigorous methodologies in evaluating land and crop productivity. Zhang *et al*. (2015) discuss the environmental trade-offs of intensive farming, particularly in nitrogen management and sustainable intensification. They advocate for a transformation of agricultural practices to minimize ecological degradation while ensuring productivity. Collectively, this cluster illuminates a crucial research frontier: balancing agricultural intensification with ecological integrity to ensure resilient, sustainable and equitable food systems in a changing world.

Cluster 5 (Purple)

Deep Learning Applications for Smart Diagnosis in Rice Crop Health. This cluster centers on the emerging integration of deep learning technologies in rice disease detection, reflecting a transformative trend in precision agriculture. The highlighted studies focus on the development and optimization of Convolutional Neural Networks (CNNs) and other AI techniques for automated, accurate and early diagnosis of rice plant diseases. Lu *et al*. (2017) and Latif *et al*. (2022) explore CNN-based approaches that leverage high-resolution image data to detect a wide range of rice leaf pathologies, showcasing the ability of deep learning to outperform traditional methods in terms of speed and accuracy. These studies serve as a foundation for more recent works that emphasize model enhancement and fusion techniques. Patil and Kumar (2022) introduce Rice-Fusion, a multi-modality data fusion framework that combines diverse data sources, pushing the boundaries of smart farming solutions. Ramesh and Vydeki (2020) add value by incorporating the Jaya optimization algorithm into deep neural networks, leading to improved feature extraction and classification accuracy. Zhou *et al*. (2019) investigated hybrid models, integrating CNNs with machine learning classifiers like Support Vector Machines and object detection models like Faster R-CNN, enabling more precise localization and identification of disease-infected areas. Altogether, this cluster illustrates a significant shift toward AI-driven crop health monitoring systems, particularly in rice production. These intelligent frameworks not only reduce the reliance on manual inspection but also support scalable, cost-effective disease management, paving the way for future innovations in automated agriculture.

The following Table 4 presents the summary of the co-citation analysis with cluster number and color, labels, number of publications and representative publications.

Co-word analysis

Co-word analysis was conducted using author keywords and index terms. From 16,887 keywords, 60 met the minimum occurrence threshold of 75, resulting in four thematic clusters. Table 5 lists the top 15 keywords based

Table 4: Co-citation clusters on agriculture and technology.

Cluster no and color	Cluster label	Number of publications	Representative publication
1 (Red)	Technological innovations and sustainability in agriculture	17	Hanafi *et al.* (2023); Hazmi *et al.* (2023); Sharma and Sisodia (2021); Chaudhary and Kumar (2022)
2 (Green)	AI-driven precision agriculture and automation	13	Hoque and Padhiary (2024); Babatunde *et al.* (2025)
3 (Blue)	Sustainable agriculture and climate-responsive farming systems	8	Steenwerth *et al.* (2014); Haldar and A (2023); Sharma and Sisodia (2021)
4 (Yellow)	Water resource management and climate-resilient crop productivity	6	Kourgialas *et al.* (2024); Chouhan *et al.* (2023); Soujanya and Gurjar (2024)

on occurrence and total link strength, with “rice” “agriculture,” and “remote sensing” emerging as dominant terms.

Fig 4 presents the network structure of the co-word analysis. It visibly shows three clusters representing three different themes. In accordance with the author’s inductive interpretation, the three clusters are assigned the appropriate labels.

Cluster 1 (Red)

Technological innovations and sustainability in agriculture

Recent bibliometric analyses reveal key trends in sustainable agriculture research. Studies highlight a focus on eco-efficient practices, climate change mitigation and technological advancements (Hanafi *et al*., 2023; Hazmi *et al*., 2023). Emerging themes include organic farming, soil health, biodiversity conservation and integrated pest management (Hazmi *et al*., 2023). Research clusters emphasize sustainable agriculture, factors affecting crop yield and plant growth fundamentals (Sharma and Sisodia, 2021). Technological frameworks, such as molecular breeding, genetic engineering and gene editing, are being developed to address agricultural challenges and increase crop yields (Chaudhary and Kumar, 2022). The integration of artificial intelligence and machine learning is revolutionizing crop management and environmental resilience (Chaudhary and Kumar, 2022). These studies underscore the interdisciplinary nature of sustainable agriculture research, incorporating biological sciences, environmental engineering and policy studies to foster sustainable and environmentally friendly agricultural systems (Hanafi *et al*., 2023; Hazmi *et al*., 2023).

Cluster 2 (Green)

AI-Driven precision agriculture and automation

Recent research highlights the transformative impact of AI and automation in precision agriculture. AI-powered solutions have improved crop monitoring accuracy by 30-50% and increased yields by 5-15% while reducing water and fertilizer use by 25-40% and 30-40%, respectively (Hoque and Padhiary, 2024).

Cluster 3 (Blue)

Sustainable agriculture and climate-responsive farming system

Sustainable and climate-smart agriculture (CSA) are crucial approaches to address food security challenges in the face of climate change. These strategies focus on enhancing productivity, resilience and sustainability of agricultural systems while reducing environmental impacts (Steenwerth *et al*., 2014). Key elements include soil health management, biodiversity conservation and climate adaptation techniques (Haldar and A, 2023). Bibliometric analyses reveal three main research focus areas: sustainable agriculture, factors affecting crop yield and basic plant research (Sharma and

Table 5: Top 15 keywords in the co-occurrence of key words analysis.

Rank	Keyword	Occurrences	Total link strength
1	Rice	744	3781
2	Agriculture	706	3662
3	Article	241	2328
4	Crops	393	2260
5	Remote sensing	456	2133
6	Crop production	308	1858
7	Nonhuman	201	1837
8	Oryza	188	1766
9	Cultivation	281	1684
10	Climate change	287	1591
11	China	203	1338
12	Fertilizers	183	1298
13	Procedures	121	1267
14	Food supply	190	1264
15	Soil	106	1199

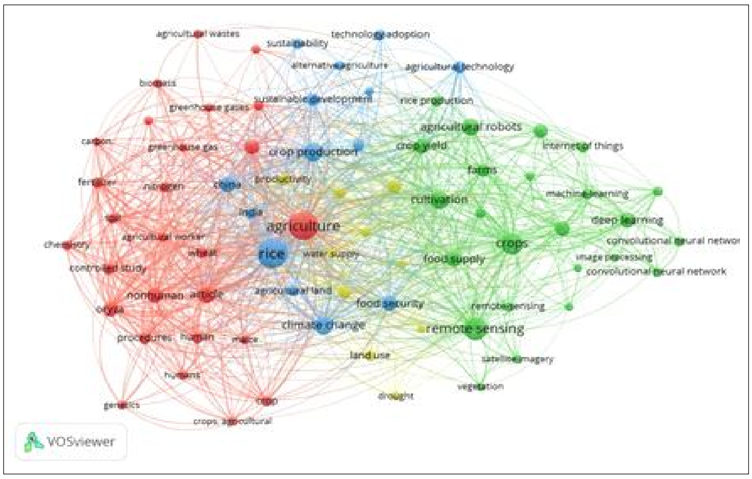

Fig 4: Co-word analysis of agriculture and technology.

Sisodia, 2021). Addressing these challenges requires comprehensive education, supportive policies and collaboration among stakeholders to ensure long-term food security and agricultural resilience (Haldar and A, 2023; Steenwerth *et al*., 2014).

Cluster 4 (Yellow)

Water resource management and climate-resilient crop productivity

Water resource management is crucial for climate-resilient crop productivity, especially in drought-prone areas. Adaptive strategies are needed to address water scarcity and erratic precipitation patterns caused by climate change (Kourgialas *et al*., 2024). Climate-smart water technologies, including hydrogel application and the SWAT method, are recommended for sustainable agriculture in water-limited regions (Chouhan *et al*., 2023). Agronomic strategies such as using drought-resistant crop varieties, soil moisture conservation techniques and optimized irrigation methods can enhance water-use efficiency in crops (Soujanya and Gurjar, 2024). An integrated approach combining genetic, agronomic and technological innovations is essential for maintaining crop productivity in drought-vulnerable areas. Policy support and farmer education are necessary to promote the widespread adoption of these water management strategies (Soujanya and Gurjar, 2024). A summary of the co-word analysis is presented in Table 6, comprising cluster number and color, cluster labels, number of keywords and representative keywords.

The findings confirm that the Digital Agricultural Revolution and Agriculture 4.0 are central themes shaping contemporary agricultural research. The bibliometric patterns show a strong shift from conventional farming toward data-driven, technology-enabled systems aimed at sustainability, productivity and climate resilience (Bertoglio *et al*., 2021; Fasciolo *et al*., 2024). The dominance of AI, IoT, UAVs and remote sensing in citation, co-citation and co-word analyses indicates that digital tools are no longer peripheral but foundational to modern agricultural science. The identified clusters highlight how research has evolved from isolated technology adoption toward integrated digital ecosystems. High-impact studies emphasize climate-smart agriculture, site-specific management and real-time monitoring, reflecting practical demands for efficiency under climate uncertainty. The prominence of total factor productivity studies further indicates that digital technologies are increasingly evaluated through measurable economic and performance outcomes, especially in developing regions (Kryszak *et al*., 2021). Importantly, the bibliometric structure reveals a gap between technological development and implementation-focused research. While technology transfer literature has expanded, fewer studies address institutional readiness, farmer adoption barriers and policy alignment. This suggests

Table 6: Summary of co-occurrence analysis on agriculture and technology.

Cluster no and color	Cluster label	Number of key words	Representative Key words
1 (Red)	Technological innovations and sustainability in agriculture	744	Agricultural wastes, agricultural worker, agriculture, article, biomass, carbon, chemistry, controlled study, crop, crops, agricultural, environmental technology, fertilizer, fertilizer application, fertilizers, genetics, global warming, greenhouse gas, greenhouse gases, human, humans, maize, nitrogen, nonhuman, oryza, procedures, soil, soils, wheat
2 (Green)	AI-driven precision agriculture and automation	706	Agricultural robots, artificial intelligence, automation, convolutional neural network, crop yield, crops, cultivation, decision making, deep learning, farms, food supply, forecasting, image processing, internet of things, learning systems, machine learning, precision agriculture, remote sensing, rice production, satellite imagery, vegetation
3 (Blue)	Sustainable agriculture and climate-responsive farming systems	456	Agricultural land, agricultural technology alternative agriculture, China, climate change, crop production, farming system, food security, India, rice, sustainability, sustainable agriculture, sustainable development
4 (Yellow)	Water resource management and climate-resilient crop productivity	393	Drought, grain (agricultural produce), irrigation, land use, paddy field, paddy fields, productivity, soil moisture, water management, water supply

a need to move beyond technical innovation toward socio-economic and governance-oriented research (Bengoa *et al*., 2020). The results demonstrate the growing importance of precision agriculture for food safety, sustainability and resource efficiency (Xu *et al*., 2024). The clustering of research around AI-driven decision-making, remote vegetation monitoring and deep learning highlights strong opportunities for automation and predictive analytics in agriculture. Leading contributions from the U.S., China, India and Iran reflect global investment in digital agriculture research (Ruiz-Real *et al*., 2020). For policymakers, the findings emphasize the need for supportive digital infrastructure, data governance frameworks and capacity-building initiatives. For practitioners, the results highlight technologies with proven research momentum, such as IoT-enabled monitoring and AI-based crop diagnostics. For researchers, the clusters provide a roadmap for aligning future studies with high-impact themes while addressing underexplored socio-economic dimensions (Xu *et al*., 2024; Rusdiyana *et al*., 2024). Despite its contributions, this bibliometric review has limitations. The analysis relies on Scopus-indexed journal articles, which may underrepresent regional studies and non-english publications. Although advanced science mapping tools were applied, bibliometric methods primarily capture publication patterns rather than on-field effectiveness or adoption outcomes (Chen *et al*., 2020). Existing studies focus heavily on technological capabilities, while operational challenges, policy impacts and farmer-level adoption remain less explored (Latino *et al*., 2022; Yousaf *et al*., 2023). Future research should integrate bibliometric insights with empirical and operational studies to better understand real-world implementation. Greater attention is also needed on interdisciplinary approaches that connect digital innovation with economic viability, institutional support and sustainability outcomes (Chen *et al*., 2020).

CONCLUSION

This study presented a bibliometric review and provided valuable insights into the evolution and future directions of agriculture and technology research. The trends in this field highlighted the growing role of digitalization, advanced information and communication technologies, artificial intelligence and blockchain technology in transforming agricultural systems. These analyses identified key research clusters, including precision agriculture, smart agriculture, remote sensing and climate-smart agriculture. Common themes across studies included the application of technologies such as unmanned aerial vehicles, wireless sensor networks, machine learning and blockchain to enhance agricultural productivity, sustainability and supply chain management. Understanding the convergence of agriculture and technology was found to be essential for sustaining the agricultural economy.

Disclaimers

The views and conclusions expressed in this article are solely those of the authors and do not necessarily represent the views of their affiliated institutions. The authors are responsible for the accuracy and completeness of the information provided, but do not accept any liability for any direct or indirect losses resulting from the use of this content.

Funding

The author(s) received no financial support for the research, authorship and/or publication of this article.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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