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Review Article

A Bibliometric Review of Data Science in Smart Farming

Omprakash Mandge[1], Suhasini Vijaykumar[2]

[1]*Institute of Computer Science, Mumbai Educational Trust, Maharashtra, India.*
[2]*Department of MCA, Bharati Vidyapeeth Institute of Management and Information Technology, Maharashtra, India.*

[1]*Corresponding Author : omprakashm_ics@met.edu*

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Abstract *- Smart Farming has transformed the agricultural sector, resulting in extensive agronomic developments. Using advanced technology and insights-driven solutions to streamline agricultural processes and enhance overall farm productivity is known as "smart farming." Because data science enables the gathering, processing, and evaluation of vast amounts of farm-generated data, it is essential for smart farming. These data sources include satellite imagery, weather data, soil sensors, machinery data, crop health diagnostics, and market trends. Data science techniques empower farmers to make informed decisions by providing actionable insights into farming, from crop planning to yield prediction. The study employs quantitative and qualitative methods to examine key trends, influential publications, and emerging data science and smart farming research areas. It discusses various factors, including publication patterns, reference sources, prominent countries, significant authors, impactful publications, networks, emerging themes, and trending topics, focusing on India. The outcomes emphasize the use of data science in smart farming. This study proposes a design cycle for data science-driven automation and a novel and multi-phase framework for efficient agriculture.*

Keywords *- Smart farming, Data science, Bibliometric analysis, Sustainable farming, Precision agriculture.*

1. Introduction

The global population of 7.6 billion is projected to increase by more than 2.2 billion to over 9.8 billion by 2050 [1]. This growth is expected to continue, with a projected population of 11.2 billion by 2100. These demographic changes profoundly impact global resources, economic development, and environmental Sustainability. This will only significantly increase food demand and widen the gap between supply and demand.

However, increasing urbanization restricts the increase in arable land for farming. The shrinking availability of farmland has reduced productivity and put enormous pressure on natural resources. Climate change, characterized by increased floods and droughts, has also heightened the pressure on agricultural productivity [2]. The 2024 Global Agricultural Productivity (GAP) Report shows worrying trends. While agricultural TFP (total factor productivity) averaged 1.9% per year from 2001 to 2010, it declined to 0.7% between 2013 and 2022. This reduction is much less than the 1.91% yearly TFP growth rate estimated to meet agricultural needs by 2050, as shown in Figure 1. This rate falls significantly short of the estimated 1.91% annual TFP growth required to meet agricultural demands by 2050, as shown in Figure 2. The TFP measures the efficiency of agricultural output relative to the combined inputs (land, labor, capital, and materials) used in production. The slowdown in productivity growth has created significant challenges for meeting the rising demand for food from one perspective and achieving environmental sustainability goals from the other. This highlights the urgent need to bridge the "valley of death, the divide between creating agricultural innovations and their adoption by farmers. This gap must be closed to boost productivity and meet growing food demands in the coming decades. “Smart farming”, also referred to as “Precision agriculture”, aims to revolutionize traditional farming practices by leveraging data science technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL).

These advances enable informed decision-making throughout the crop lifecycle, enhancing crop planning, soil productivity, yield forecasting, weed management, and pest control [3]. Smart farming is not just one technique but a collection of methods and strategies aimed at enhancing precision and agricultural productivity [4-6]. This shift toward smart farming can significantly increase the efficiency and Sustainability of agriculture. These advancements are particularly crucial for India, where agriculture supports the livelihoods of the majority and is responsible for around 17% of the country's GDP. Despite being the second-largest producer of agricultural goods globally, India's average crop yields lag 50–70% behind those of the top producers worldwide. Key agrarian outputs, such as food, industrial raw materials, and fuel, play a crucial role in nation-building [7].

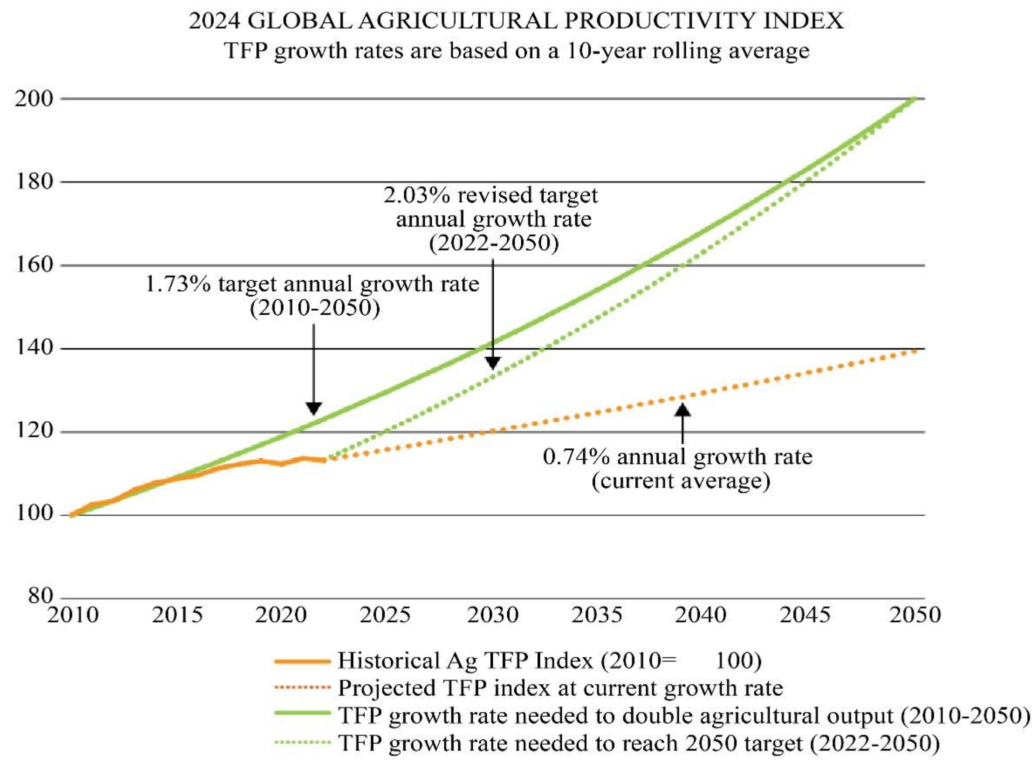

Fig. 1 Global productivity report 2024 [2]

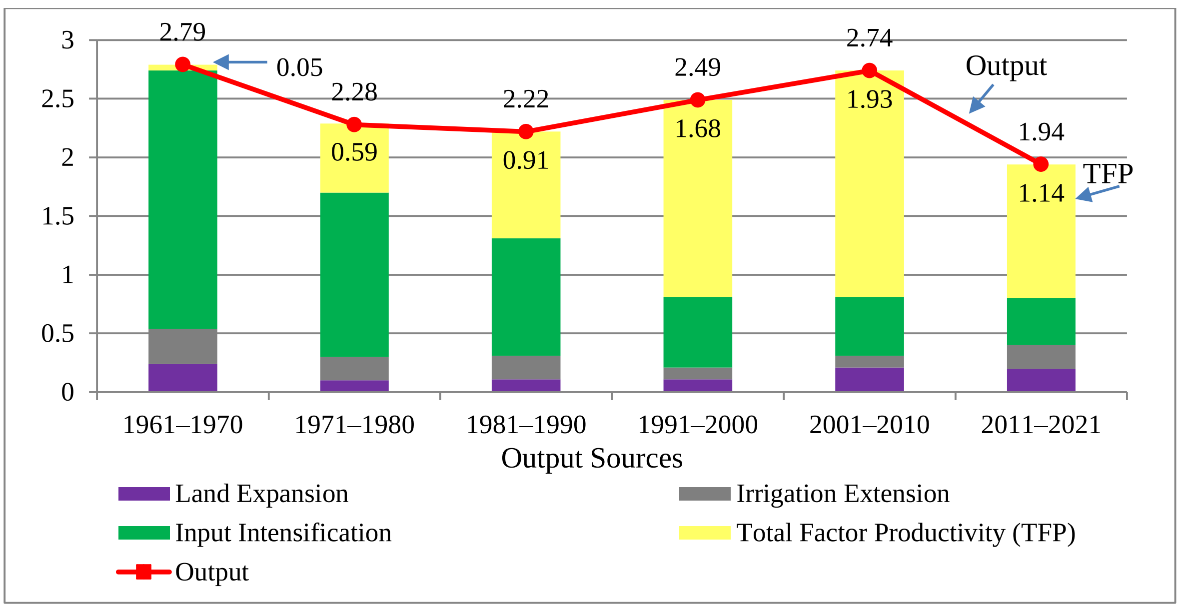

Fig. 2 Average annual growth rate

India's expanding population, rapid urbanization, and growing economy intensify food demand. While projections suggest that by 2030–31, the nation will achieve production reliability in rice and wheat, commodities such as pulses, oilseeds, and fruits are expected to face supply-demand gaps [8, 9]. Additionally, significant postharvest losses aggravate these challenges. Recent studies indicate that India loses approximately 40% of its horticultural produce annually, with fruits and vegetables particularly susceptible due to their short shelf life [10]. Addressing these issues requires substantial reforms and investments in agricultural practices, infrastructure, and supply chain management to ensure food security in the coming decades. Indian agriculture faces several significant challenges, including the continued reliance on traditional farming methods, a heavy reliance on personal experience, and limited adoption of modern technologies, particularly in remote areas. These factors make it difficult for farmers to select suitable crops for their farms accurately. Unpredictable climate fluctuations further complicate these issues, resulting in reduced crop yields. Inadequate farming practices, low-yielding crop varieties, and fragmented landholdings contribute to yields 35–50% below global standards. Mechanization in developed countries exceeds 90%, whereas in India, it remains below 50%. Furthermore, nearly 40% of the food produced in the country is lost or wasted [11].

India must enhance crop productivity through data-driven solutions to meet the increasing demand for food and ensure the effective use of natural resources. It is necessary to design and implement a practical analytical framework that supports farmers at each phase of the agricultural lifecycle. This solution can increase yields, encourage sustainable farming practices, and provide practical, area-specific recommendations to empower Indian farmers by integrating innovative approaches.

“Data science is a multidisciplinary field that uses scientific methods, procedures, algorithms, and systems to extract information from organized, semi-structured, and unstructured data”. It includes data extraction, preparation, analysis, visualization, and management [12, 13]. Data science encompasses statistics, AI, ML, big data technologies, and DL. The component and field-based definition of data science [13] is stated below.

Data science=statistics + informatics + computing + communication + sociology + management| data + environment + thinking (| means conditional on)

AI is capable of mimicking human behavior. ML division of AI focuses on enabling machines to improve and adapt by examining data using statistical methods. DL is a specialized area within ML that employs algorithms designed to simulate human thought processes by learning from examples. AI in smart farming tackles issues related to Sustainability by utilizing ML, DL, and time series analysis for crop selection, yield prediction, and demand forecasting [14]. AI-driven techniques optimize farming practices and emphasize the role of predictive algorithms in addressing future food security concerns. Precision Agriculture leverages ML to address challenges in crop yield prediction by analyzing complex datasets that include climate, soil, and fertilizer data. These models use historical data to recognize patterns and accurately predict future outcomes. Despite advancements, further algorithmic and data handling improvements are essential for enhanced performance [15]. DL models CNN, RNN, AlexNet, and ResNet are widely utilized in crop yield predictions. However, there is a need for advanced DL techniques to enhance model performance and reduce inference time for real-world applications [16]. The advancement of IoT technology and the increased accessibility of sensor data are key factors driving the adoption of smart farming practices. Figure 3 depicts the cyber-physical management system for smart farming. Data are gathered from diverse sources, including sensors, on-field robots, and satellite imagery, and are systematically stored in cloud-based systems. A critical human element remains integral, ensuring continuous analysis and effective planning for utilizing and managing these data [17, 18].

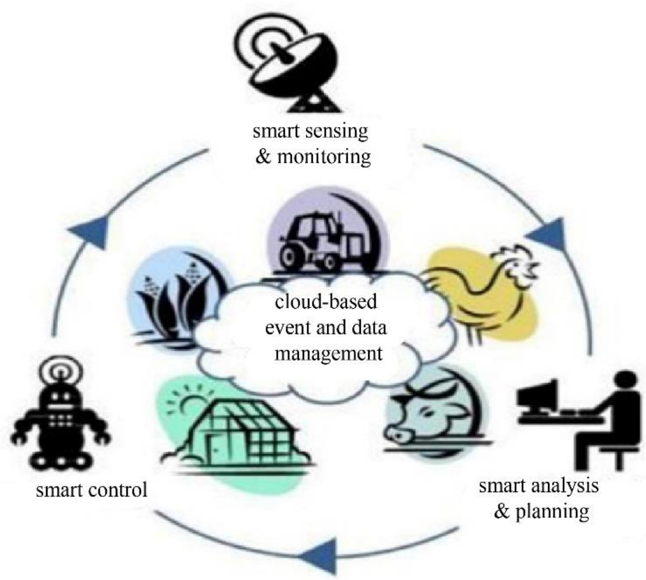

Fig. 3 Cyber-physical system for smart farming [19]

Smart farming generates massive amounts of data that require advanced storage and management, utilizing data science. Data science models and design automation frameworks that apply during plant production and the entire smart farming supply chain. Despite significant advancements in AI-driven smart farming, several research gaps remain unaddressed. Current DL models are widely applied in crop yield prediction; however, their real-world deployment remains limited due to high inference times and insufficient optimization for practical agricultural settings.

Moreover, the massive and heterogeneous data generated from sensors, satellites, and robotic systems present challenges regarding scalable data handling, integration, and real-time preprocessing. Most ML models focus on region- or crop-specific conditions, which restricts their generalizability across diverse agricultural environments. Additionally, the application of time series forecasting for dynamic and real-time agricultural decision-making, particularly in yield and demand prediction, remains underexplored. Furthermore, the adoption and effectiveness of data science techniques in agronomy lack sufficient empirical evaluation, particularly from the perspective of practitioners. To systematically identify and address these gaps, this study employs Bibliometric analysis. By mapping research trends, citation networks, key contributors, thematic clusters, and underexplored areas, Bibliometric analysis provides a complete summary of the current state of research. It helps identify overlooked topics, assess the evolution of technological focus areas, and uncover potential interdisciplinary opportunities that inform future research directions in smart farming. This research examines the acceptability of data science techniques in agronomy through a systematic literature review strategy with two primary components: 1) Conducting a comprehensive Bibliometric analysis of previous research to identify gaps and suggest potential solutions. 2) Adapting the outcomes to the context of smart farming in India.

2. Methodology

Bibliometric analysis is a quantitative, computer-assisted technique for assessing bibliographic data to identify key publications, notable authors, and leading institutions [20, 21]. It helps evaluate the effect and influence of research articles, authors, journals, and institutions by examining citation patterns, publication counts, keywords, and other metrics.

This technique is widely used to find research trends, influential works, and knowledge gaps across various disciplines.

A substantial dataset of bibliographic records was analyzed to uncover patterns, trends, and emerging research in smart farming. The bibliometric analysis was conducted using the methodology proposed by [22]. The process is organized into three main phases, as shown in Figure 4, which are detailed in the following sections.

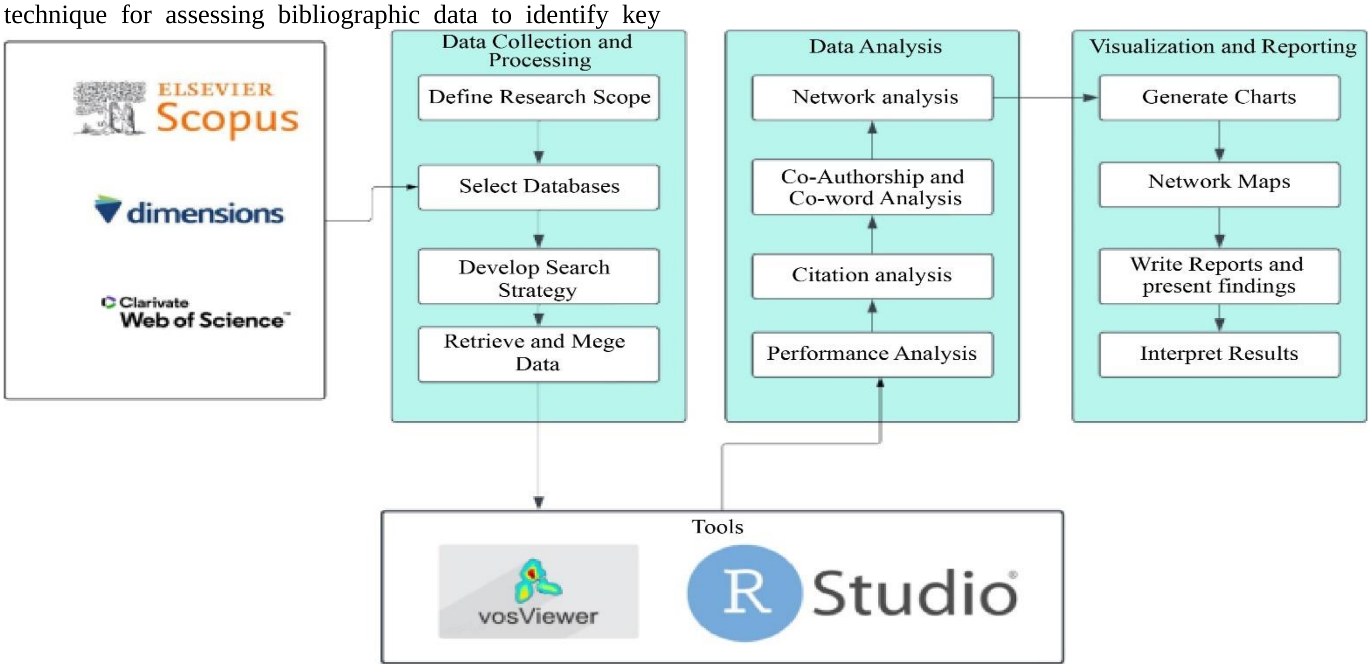

Fig. 4 Bibliometric analysis workflow

2.1. Data Collection and Processing

This study aims to identify key themes, publication trends, and information gaps to inform future research and policy guidelines. The Bibliometric review addresses the following Research Questions (RQs) related to data science in smart farming, adaptation, and agricultural Sustainability, which have remained unexplored.

RQ 1: What are the trends in the pblication of data science-driven smart farming research over the last two decades, and which nations and institutions have led the way in research on data science applications in smart farming?

RQ 2: What are the major research themes, data science techniques, and latest technologies driving advancements in smart farming?

RQ 3: Which crops are commonly studied in data science-driven smart farming, and how are data science techniques used for yield prediction and resource optimization?

RQ 4: How does Bibliometric analysis shape research priorities and address gaps in data science-driven smart farming?

The study considers several well-established libraries and databases for Bibliometric analysis, including Scopus, Web of Science, and Dimensions [23]. These databases are selected due to their comprehensive coverage, accuracy, and widespread use in academic research. Google Scholar, although widely accessible, was excluded from the study due to its limitations in data reliability and consistency, which can impact the quality of citation metrics and analysis [24]. However, papers from other sources are considered. The search is based on the relevant concepts at a basic level as applied directly within the scope of this review. First, keyword searching is conducted across various research articles to extract bibliographic information. The search focuses on key themes in smart farming, including core areas such as precision farming, smart agriculture, and data-driven techniques, with a special emphasis on trending technologies -IoT, ML, and big data. Application-specific keywords address crop yield prediction, pest management, and fertilizer optimization, whereas region-specific terms highlight studies on agriculture in India and localized systems within the country. Emerging trends and methodologies, including drones, blockchain, computer vision, and DL models, provide knowledge about the future of innovative farming.

The keywords used for the study are combinations of these themes, as follows:

- Data Science smart farming or precision agriculture
- ML & smart farming or precision agriculture
- Deep Learning smart farming or precision agriculture
- Artificial Intelligence smart Farming or precision agriculture
- Big Data Analytics smart farming or precision agriculture
- Automation smart farming
- Smart Farming or PA & Crop Recommendation
- Smart Farming crop yield Prediction or precision agriculture

A search strategy is developed by starting with basic keywords and refining the search results using specific exclusion criteria. This process guarantees that only the most appropriate articles are selected. The search is conducted across three different databases, and results are generated in CSV format for the Scopus and Dimensions databases and in TXT format for the Web of Science [25-27]. Figure 5 shows the search strategy for the Scopus database. The exact process is applied to the other two databases, Web of Science and Dimensions. Table 1 shows the search keywords and the number of documents retrieved after applying exclusion criteria.

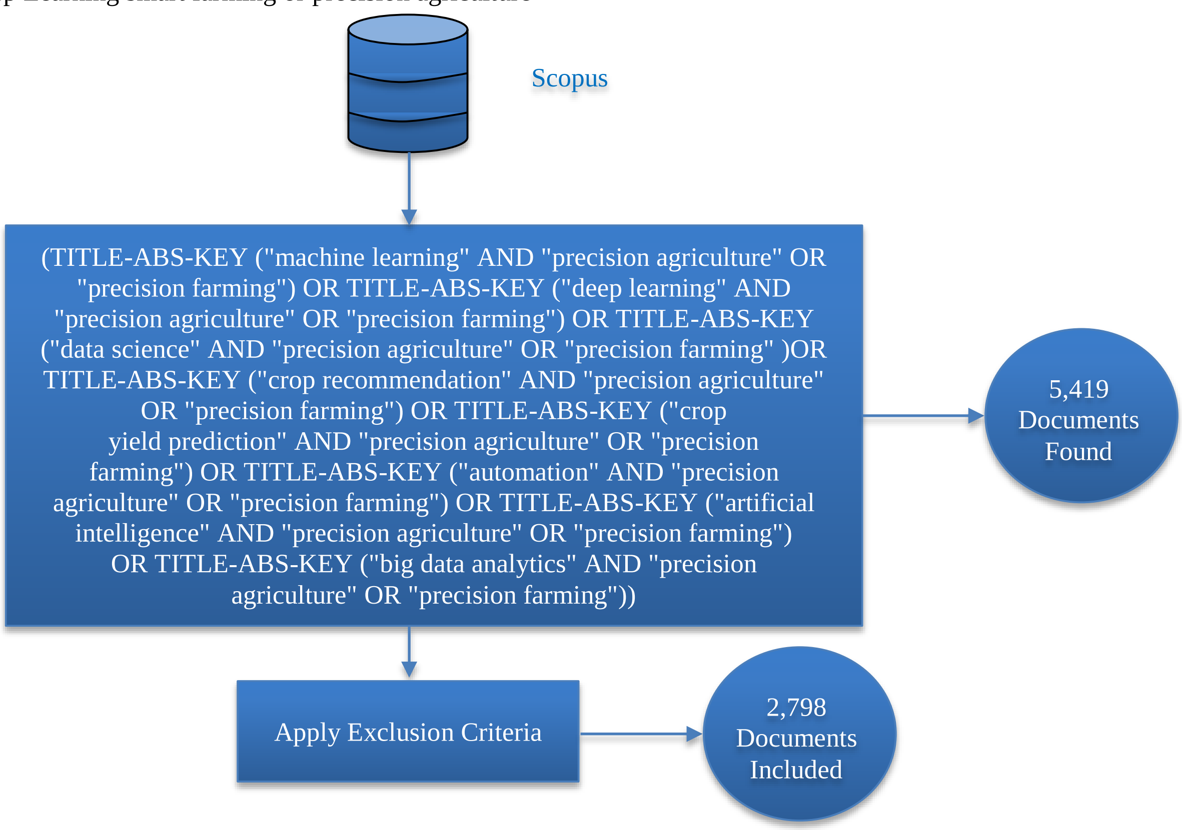

Fig. 5 Document retrieval flow

Publications are excluded based on several criteria to ensure relevance and quality. First, only English-language publications are considered, excluding those published in languages other than English. Second, publications unrelated to agriculture are omitted to maintain focus on the research domain. Third, studies published before 1995 are excluded to ensure contemporary relevance. Duplicate papers are removed to avoid redundancy. Open-access papers are included, aligning with the study's scope. Finally, a preliminary analysis and screening process is conducted to eliminate irrelevant papers and review articles that do not contribute to the research.

Table 1. Documents retrieved from each database after applying the search keyword and exclusion criteria

Database	Documents after Exclusion Criteria
SCOPUS	2798
Dimensions	1688
Web of Science	8,321

A total of 12,807 papers are considered for further studies. The datasets from Dimensions, Web of Science, and Scopus are combined for unified analysis, with careful handling to ensure accuracy and avoid duplication. Data from all three databases is exported in compatible formats, such as CSV or BibTeX, including key fields like DOI, title, authors, publication year, and journal. Data normalization is performed by standardizing fields such as author names, journal titles, and publication dates while ensuring consistent formatting and encoding.

Duplicates are identified and removed using unique identifiers, such as DOIs, or by matching records based on title, authors, and publication year, with fuzzy matching employed to account for variations in these fields.

Non-duplicate records are merged, and for duplicates, the complete version is retained, or complementary information is integrated, such as richer citation data from Scopus or funding data from Dimensions. An R script is designed to combine the data from all three databases, following the process shown in Figure 6. This study used 10,265 documents for bibliometric analysis. R Studio and VosViewer are utilized to perform the analysis. A separate dataset is prepared by filtering out all other information and retaining only the papers related to India.

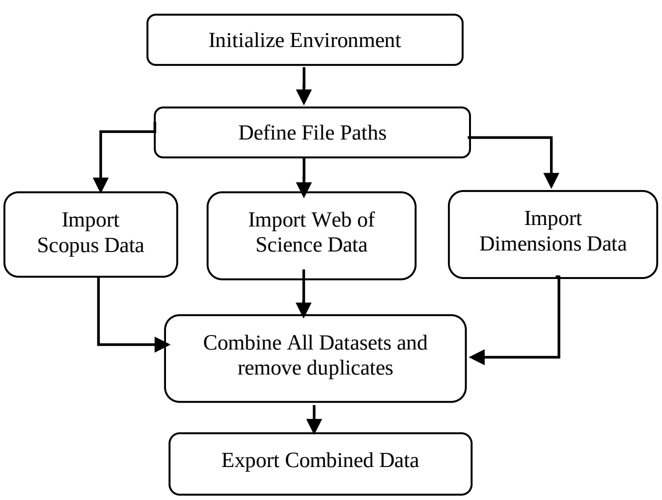

Fig. 6 Integration of data from all source databases

2.2. Data Analysis

Insights from the dataset are derived through a bibliometric analysis conducted using Biblioshiny [28] and VOSviewer [29]. The evaluation of key metrics such as productivity and the effect of leading researchers, organizations, journals, citation patterns, and nations within the domain is made feasible by Biblioshiny. To address RQ1, insights into publication growth trends over the past three decades are gained, and leading countries and institutions are identified by analyzing author affiliations and regional publication contributions.

Keyword co-occurrence maps and thematic clustering are generated using bibliometric and VoSviewer software to identify commonly used terms, research themes, and emerging technologies in the field. These methods have revealed patterns in implementing data science techniques while also illustrating the evolution of thematic focus over time. A visual and quantitative analysis of keyword connections has helped to uncover both established and emerging trends, giving a complete view of the research addressing RQ 2.

To address RQ 3, bibliographic data on study focus (e.g., keywords, abstracts, and titles) are used to determine the most frequently studied crops and farming systems. Citation analysis highlights the impactful studies addressing yield prediction and resource optimization. Bibliometric methods have helped to identify influential papers, citation networks, and collaboration patterns, helping to recognize underexplored topics, geographical gaps, and underrepresented methods. These insights address RQ 4 and guide the realignment of research priorities to address gaps and nurture interdisciplinary collaboration, ensuring a more comprehensive and impactful research landscape.

2.3. Visualization and Reporting

Through efficient reporting and visualization, bibliometric analysis via Biblioshiny and VOSviewer offers insightful information on research landscapes. Biblioshiny is used to visualize performance metrics, including the most prolific authors, influential journals, and collaborative networks. Thematic maps and charts are generated to track shifts in research focus, particularly in smart farming. VOSviewer is employed to create detailed network maps, such as citation networks highlighting key papers and keyword clusters that identify core and emerging research themes. Finally, comprehensive reports are prepared, and the results are analyzed to present a detailed scenario of the research trends.

3. Analysis and Results

This segment contains the outcomes of a bibliometric analysis conducted to investigate the usage of data science in smart farming and precision agriculture. This measurable methodology reveals the reasonable structure of these domains, monitors citation patterns, identifies emerging technologies and approaches, and highlights prospective future research possibilities. This investigation contributes to a deeper understanding of how tools from data science are revolutionizing farming practices, encompassing crop monitoring, yield prediction, resource optimization, and pest control, thereby clearing the path for more sustainable and efficient agricultural systems. Document types [30] play a decisive role in bibliometric analysis, aiding the evaluation of research trends and their impact. Research articles and reviews are primary sources, providing detailed studies and summaries of research in specific areas. Overall, 8909 research documents were considered in the current study. Book chapters offer in-depth coverage of specialized topics, presenting expert perspectives and extensive research [31]. Conference papers are among the most recent available research and offer valuable insights into emerging trends. A total of 208 book chapters and 714 conference papers are available for analysis. Editorials: Editorials comment on critical issues in a discipline. A total of 85 editorials are available in the dataset. 26 Data papers are analyzed. Data papers give information on datasets. Information from data papers can be used to reuse and validate research data. Each type of document is important for understanding the dynamics of scholarly communication and for measuring research impact across disciplines [32]. Figure 7 shows the count of different types of documents used in the study.

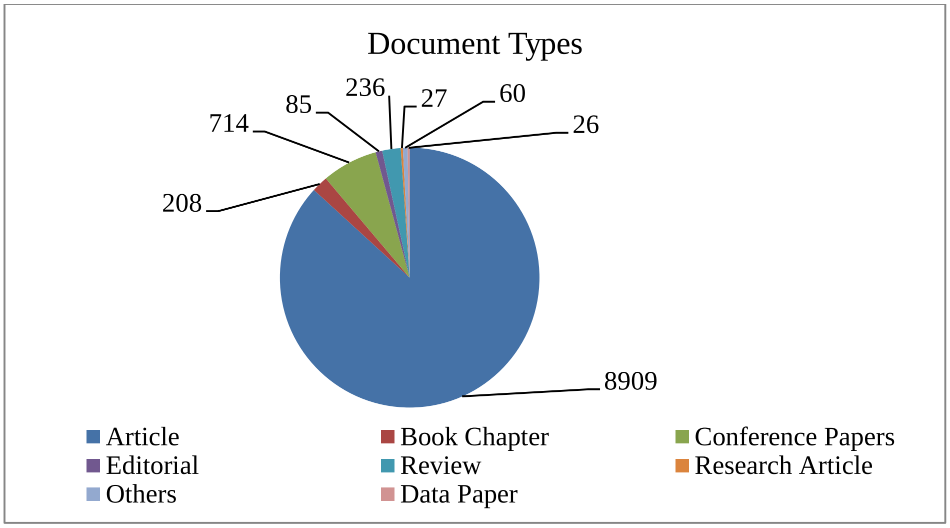

Fig. 7 Types of documents used in the study

3.1. Research Productivity Analysis

Research Productivity Analysis inspects the contributions of various research elements in bibliometric studies, whereas science mapping explores the connections among these components, enabling the evaluation of author and institutional productivity [33]. The dataset spans 3 decades, from 1995 to 2025. The dataset comprises 10,265 documents, with a yearly increase of 11.79%.

Fig. 8 Key metrics on publications, authorship, collaboration, and citation trends

The dataset has a typical age of 4.04 years, indicating that it is relatively new, and this subject is rapidly evolving and increasing in relevance. The sample's mean of citations per document is 17.58, indicating high influence. Figure 8 provides key Metrics on Publications, Authorship, Collaboration, and Citation Trends. The research in this area is highly collaborative, with an average of 5.26 co-authors per document; however, international collaboration remains limited, at just 5.699%. Policymakers can address this by promoting cross-border research initiatives and international funding programs to nurture knowledge exchange and innovation transfer. The thematic diversity is also noteworthy, with 5,240 unique keywords highlighting the field's interdisciplinary nature, ranging from AI and machine learning to agronomy and Sustainability. This suggests a need for integrated policy frameworks encouraging cooperation between agricultural scientists, technologists, data scientists, and environmental experts. Moreover, the strong average citation rate of 17.58 per document reflects this research's high impact and academic relevance, indicating that robust scientific evidence can confidently inform policy decisions. The relatively young average document age of 4.04 years suggests that the most recent research is relevant to current challenges, providing a reliable foundation for formulating adaptive and forward-looking policies. With only 194 singleauthored works among over 40,000 contributors, it is clear that the field relies heavily on team-based, interdisciplinary research. This highlights the need for environments that support collaborative research infrastructures, including shared data platforms, open-access initiatives, and cross-institutional partnerships. Overall, this analysis underscores the importance of implementing policy mechanisms that support technical research and foster international collaboration, data governance, and capacity building within the smart farming ecosystem.

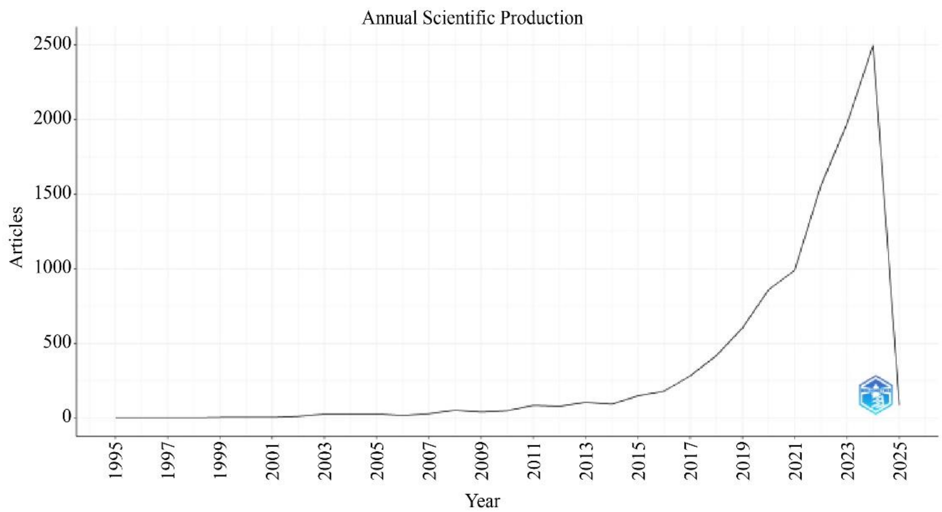

Fig. 9 Publication of papers by year

Figure 9 shows the annual publication of the papers. There has been a notable surge in publications since 2019, with a peak of 2,496 articles in 2024, indicating significant developments have occurred over the last five years. This implies that innovations in data science technologies, AI, ML, DL, CV, IoT, and increased financing for agricultural initiatives accelerate scientific and agro-industrial development. Relevant sources highlight high-impact publications, leading authors, and significant journals that shape the intellectual landscape [34]. Table 2 presents the top 10 journals based on the total number of articles published, with Remote Sensing being the only one with over 600 publications.

Table 2. Top 10 journals with number of articles

Sources	Articles
Remote Sensing	631
Computers and Electronics in Agriculture	581
Sensors	459
Frontiers in Plant Science	413
Agriculture-Basel	307
Agronomy-Basel	302
IEEE Access	245
Applied Sciences-Basel	185
Sustainability	183
Precision Agriculture	179

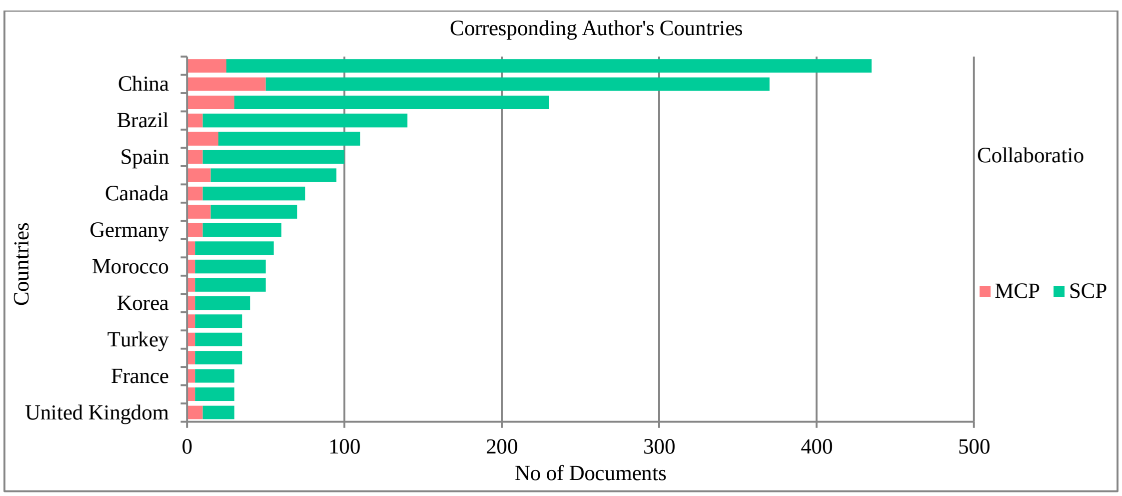

Fig. 10 Corresponding author’s countries

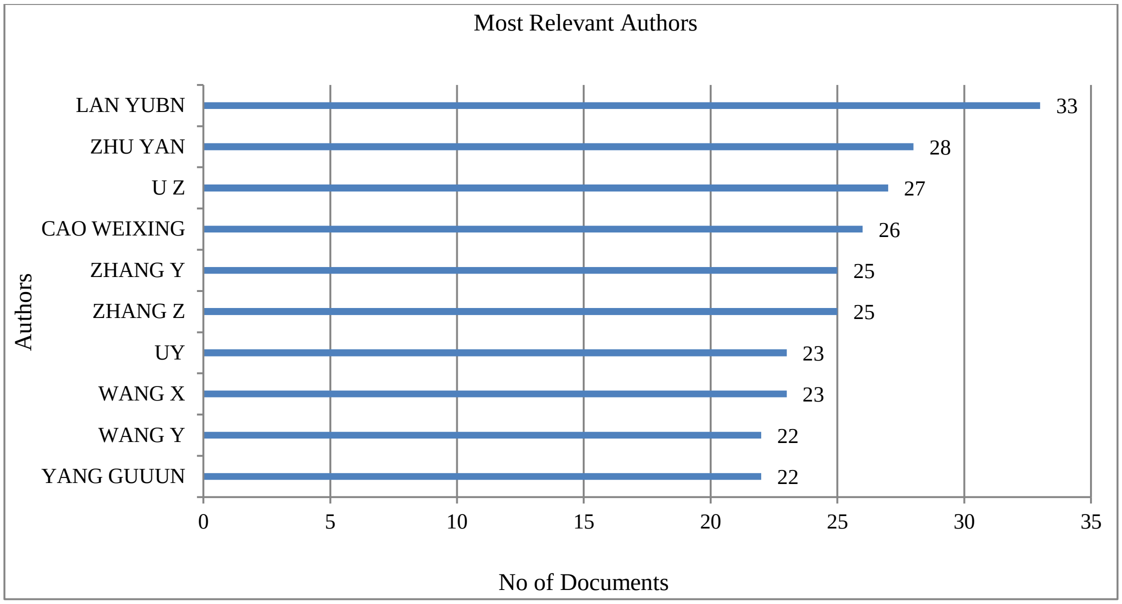

Fig. 11 Top 10 contributing authors

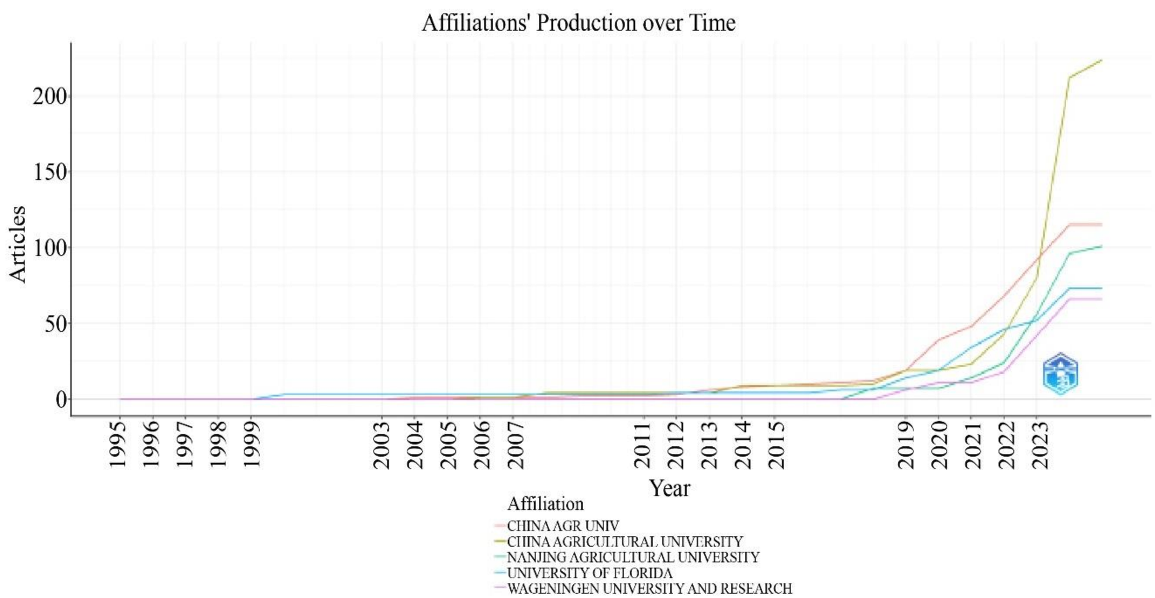

Fig. 12 Affiliations production over time

Furthermore, publications specialized in computer science and agriculture dominated the list. This study highlights progress in research within the Indian context. India contributed significantly to the research, with 411 documents under evaluation from the country, followed by China and the USA. Figure 10 illustrates the countries that contributed to the publications of the corresponding authors. Figure 11 shows the top 10 authors contributing in this area. This indicates the geographical distribution of research output, collaborations, and influence. It demonstrates that India, China, the USA, and Brazil are prominent in this research due to their focus on food security and agricultural innovation. Figure 12 illustrates the organization's contributions over time, providing insights into research organisations' history, strategic objectives, and influence on the global research landscape.

3.2. Citation Analysis

Citation analysis reveals that citations represent logical relationships between publications, formed when one publication refers to another [35]. The publications are evaluated based on the number of times they are cited. This helps identify the significant publications in the given research area. Table 3 highlights the countries that reference the highest number of documents, with the United States ranking first.

Table 3. Top cited countries

Country	TC	Average Article Citations
USA	7844	38.30
India	6487	15.80
China	6193	19.50
Germany	3502	83.40
Australia	3131	54.90
Greece	2353	49.00
Spain	2352	31.40
Canada	2278	45.60
Brazil	2160	26.00
Italy	1601	20.00

Figure 13 illustrates the average number of citations per year. The graph shows the average citations per year from 1995 to 2025, showing a general upward trend with fluctuations until around 2020. A peak in citation averages occurs between 2017 and 2020, reflecting a period of high-impact research. However, a sharp decline is observed after 2021, primarily due to citation lag, as recent publications have not yet had sufficient time to accumulate citations.

Table 4 displays the maximum cited global documents, including their publication location, the number of citations, and the annual citation count. The most frequently cited study [43], published in 2010, discusses how precision agriculture utilizes advanced technologies to optimize resources, enhance Sustainability, and increase agricultural output in value and volume.

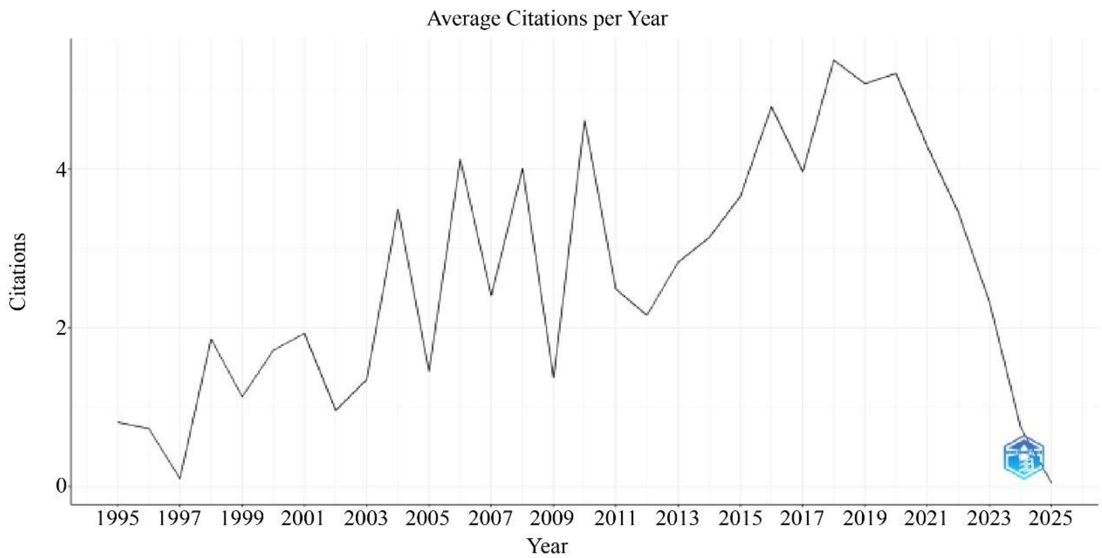

Fig. 13 Number of citations year-wise

The studies listed in the table emphasize the revolutionary impact of modern technology in PA. They stress using machine learning, wireless sensors, computer vision, and imaging technologies to enhance agricultural methods. Topics range from improving food security and crop yield prediction to disease detection and plant phenotyping using innovative tools, such as hyperspectral reflectance, vegetation indices, and UAVs. The works also underscore the significance of AI in grain crop management and fruit detection, showcasing the growing reliance on intelligent, automated systems to address agricultural challenges and improve efficiency.

Table 4. Highly cited documents

Source	Digital Object Identifier	Citations	Year-wise citations	Normalized citations
[36]	10.1126/science.1183899	972	60.75	13.16
[37]	10.1016/j.compag.2018.05.012	929	116.13	21.57
[38]	10.1016/j.compag.2005.09.003	922	46.10	11.16
[39]	10.14358/pers.70.5.627	905	41.14	11.75
[40]	10.1016/j.compag.2008.03.009	813	45.17	11.25
[41]	10.1016/j.compag.2010.06.009	770	48.13	10.43
[42]	10.1016/j.compag.2018.08.001	681	85.13	15.81
[43]	10.1016/j.compag.2007.05.008	662	36.78	9.16
[44]	10.3390/s16081222	655	65.50	13.69
[45]	10.1094/PDIS-03-15-0340-FE	650	65.00	13.58

The global citations reflect the count of citations of a document in the global dataset, regardless of source. The local citations represent the number of times a document is cited within a specific subset of the analyzed dataset, which is limited to citations from other papers in the uploaded dataset. Figure 14 illustrates the most frequently cited local documents. Journals concentrating on computer electronics and agricultural technologies are important in promoting precision agriculture research, emphasising UAVs, ML, sensors and other data science techniques.

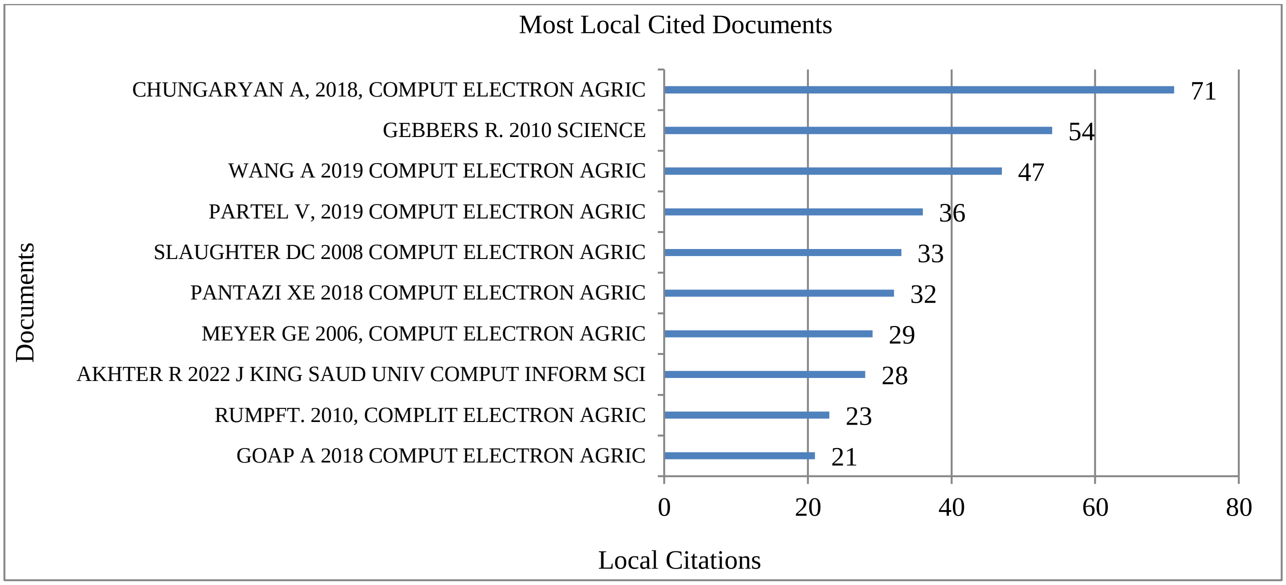

Fig. 14 most cited local documents

3.3. Keyword and Authorship Mapping

In keyword study, the focus is on analyzing "words" within the content of publications. It focuses on the contents of abstracts, titles, and keywords. Co-word analysis typically uses "author keywords," but if these keywords are unavailable, abstracts are used for word extraction [46]. A treemap generated using Biblioshiny is created to represent the hierarchical distribution of keywords from the abstracts of the papers, with a threshold value of 50. Treemap is represented using nested rectangles sized proportionally to their values, as shown in Figure 15. The treemap shows that the most frequently used keyword is 'data', indicating the data-driven modelling used in smart farming. The top 25 keywords can be grouped into Technology and Methods, Agriculture and Environment, and Research and Analysis. The "Technology and Methods" category includes precision, models, detection, accuracy, methods, learning, images, proposed, and performance. The "Agriculture and Environment" category encompasses terms like soil, crop, agriculture, yield, agricultural, plant, water, and field. The "Research and Analysis" category deals with data, study, results, and management. Coauthorship is a formal technique of working jointly [47]. Understanding how researchers network, including their affiliations, institutions, and countries, is essential. A coauthorship study of researchers from different nations is conducted using VoSviewer and is presented in Figure 16. The analysis employs an association method and generates 9 clusters comprising 65 countries.

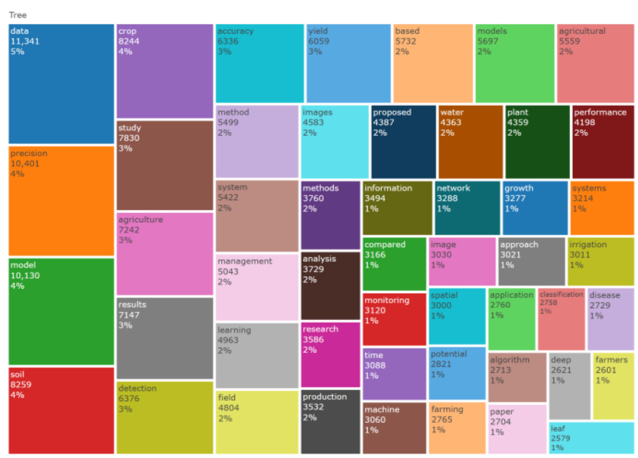
Fig. 15 Treemap of keywords in abstracts

As shown in Figure 16, nodes represent countries, with larger nodes indicating higher contributions. It is observed that authors from the USA, India, and China are among the highest collaborators. Links signify coauthorship relationships, where thicker links denote stronger collaborations. The authors from India collaborate more intensely with authors from the USA, Brazil, the UAE, Nepal, and the United Kingdom. Figure 17 shows the collaborations of authors from India. Clusters are used to group nodes based on connection strength, reflecting collaborative networks or research groups, and the analysis is performed using 9 clusters-Figure 18 shows cluster-wise densities.

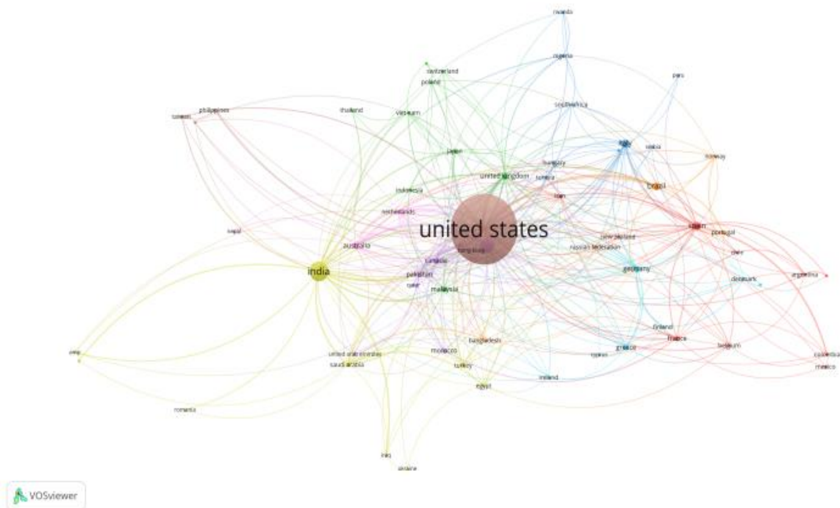

Fig. 16 Coauthorship analysis

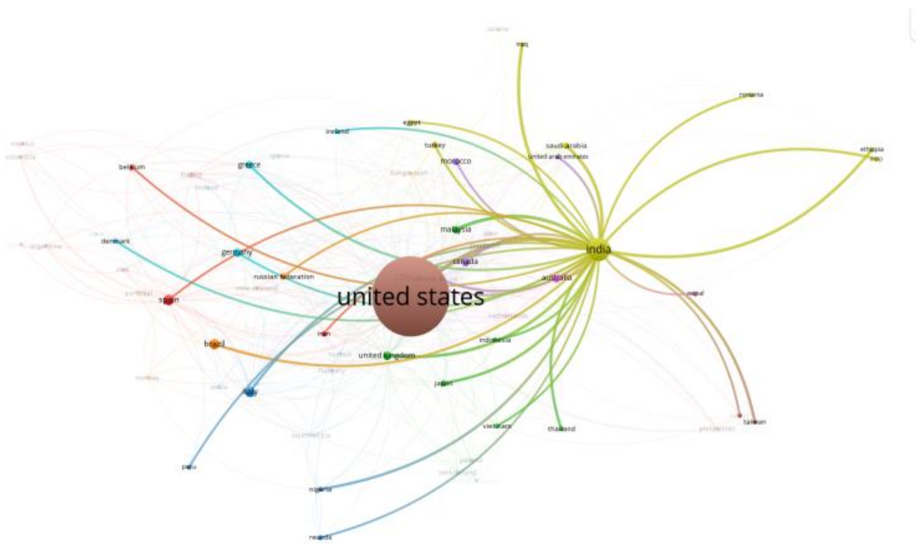

Fig. 17 Network of indian authors

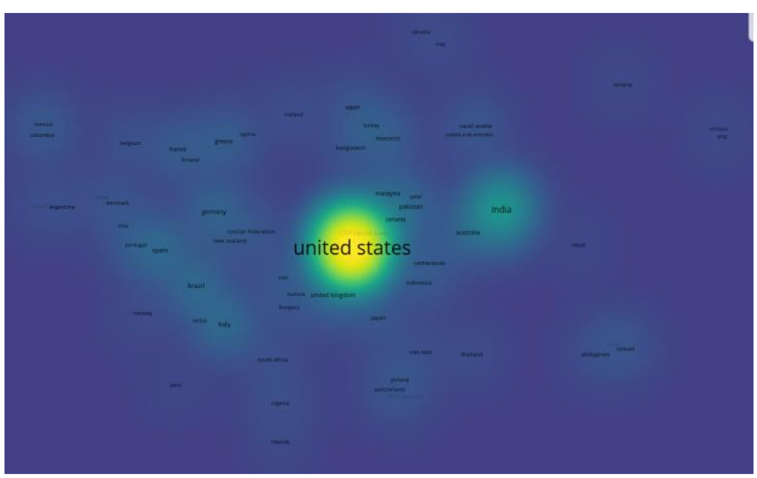

Fig. 18 Clusters visualization

3.4. Network Analysis

Network analysis examines interactions and collaborations between authors, institutions, countries, keywords, or citations [48]. Its purpose is to provide insights into the structural relationships and dynamics within a bibliometric dataset, identifying hubs, influential nodes, and the overall network structure. Network analysis focuses on any interconnected entities, including authors, institutions, keywords, or references. In-depth network analysis is performed using Biblioshiny and VosViewer, as shown in Figure 19. Network co-occurrence analysis reveals the links and significance of essential phrases in smart farming. Analysis metrics include PageRank, Betweenness and Closeness.

PageRank measures the importance of a node (e.g., keyword, author, or paper) based on the number and quality of links it receives from other nodes [49]. Betweenness measures the extent to which a node lies on the shortest path between other nodes in the network. A keyword with high betweenness (e.g., "data fusion") might connect two distinct research subfields, remote sensing and machine learning, as a bridge between them. Closeness measures how close a node is to all other nodes in the network. It reflects the efficiency or speed at which information can spread from one node to another. In author Networks, a researcher with high closeness centrality can access diverse information across the network more efficiently, making them a good collaborator. Two groups emerged from this investigation.

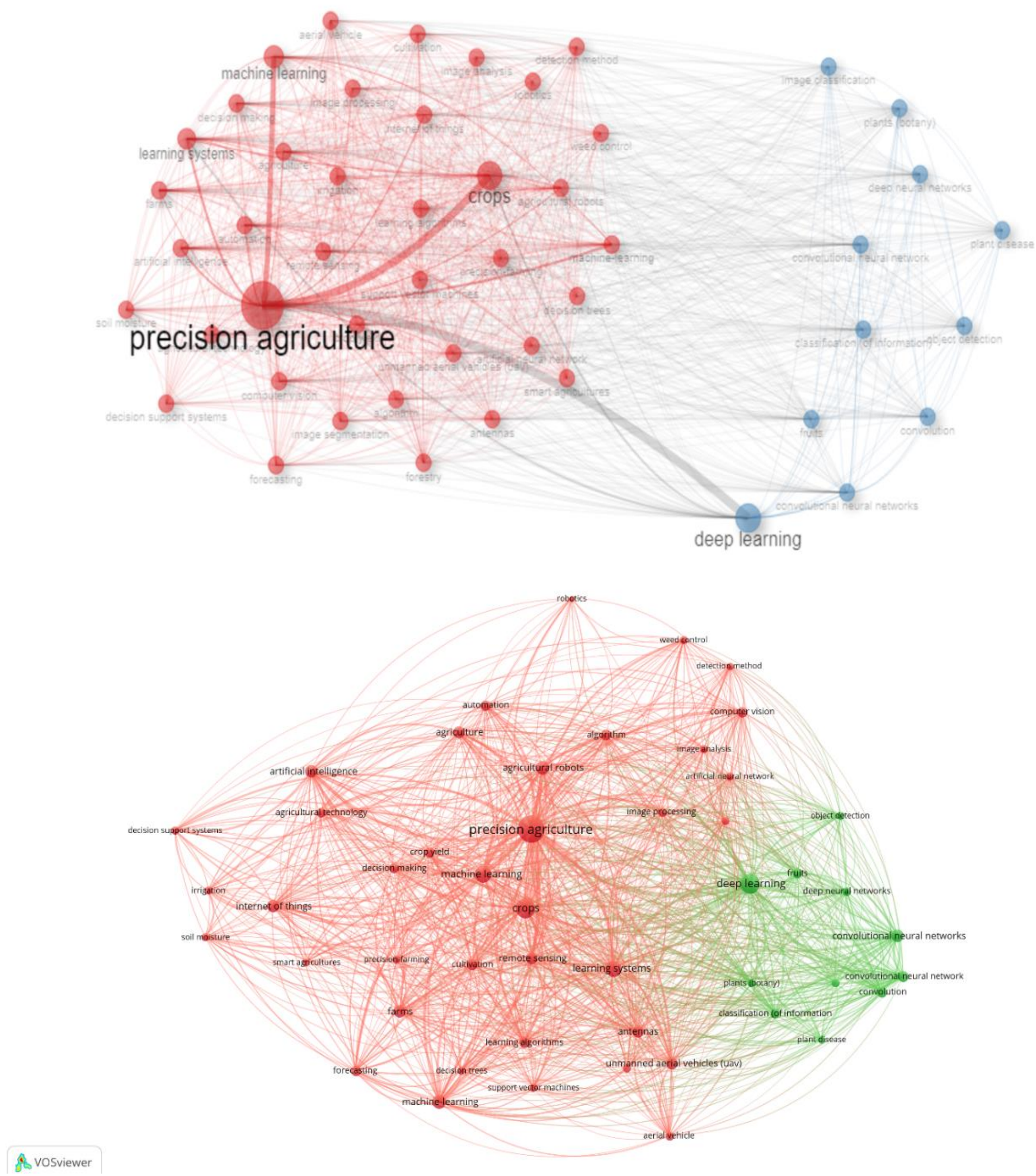

Fig. 19 Co-occurrence analysis, (a) Using bibliophily, and (b)using VOSviewer.

3.4.1. Cluster 1: Core Themes in Smart Farming

Precision agriculture stands out, with the highest betweenness (32.965) and PageRank (0.096), indicating its importance in connecting related topics and the overall significance in the research field. Other secondary but significant topics are crops (Betweenness: 8.536, PageRank: 0.056) and machine learning (Betweenness: 3.729, PageRank: 0.039). This implies an emphasis on modern crop management and monitoring technology. Moderate Betweenness and PageRank values are noted in remote sensing, artificial intelligence, and computer vision. Supporting topics include irrigation, soil moisture, decision support systems, and weed control, focusing on practical applications and challenges in precision agriculture.

3.4.2. Cluster 2: Advanced Machine Learning Techniques

Deep learning emerges as a key term in this group, with a high Betweenness score of 5.428 and a PageRank of 0.055, indicating an increasing role of deep learning in precision agriculture research. Specific techniques, including convolutional neural networks, show high betweenness at 0.490 and PageRank at 0.025, thus highlighting advanced methods for image analysis and classification. Plant disease monitoring, image classification, and object identification underline the use of ML in assessing plant health and optimizing agricultural outputs. Furthermore, the terms plants and fruits reflect the use of ML in certain plant-based agrarian studies. Trend analysis helps to understand research directions, predict future trends, and identify gaps for further exploration. Figure 20 shows the study's trend topics. The trend topics chart shows the evolution of key research terms in precision agriculture from 2004 to 2024. Recent years highlight growing interest in advanced methods like image coding, IoT, and deep learning. Term frequency is visualized by bubble size, with larger bubbles indicating more frequent usage.

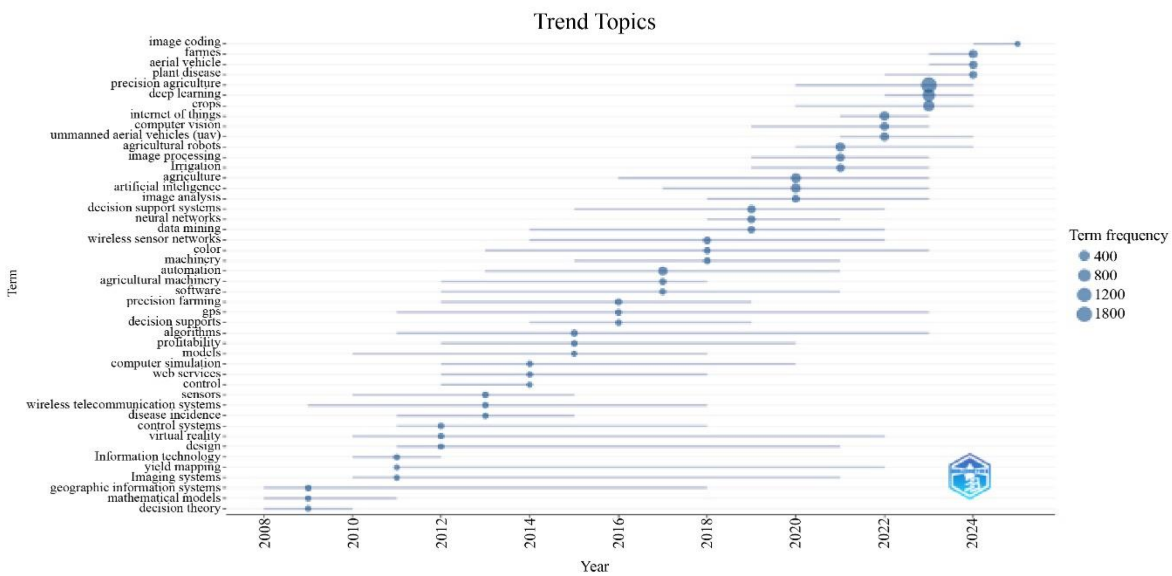

Fig. 20 Trend topics global

3.5. Bibliometric Analysis of Smart Farming in India

To focus specifically on research conducted in India, the datasets from all three databases are refined to include only publications originating from India. The filtered data are then analyzed using bibliometric techniques, including citation analysis, network analysis, and trend analysis. These analyses provide insights into India's contributions to precision agriculture research, enabling comparisons with global trends. Figure 21 highlights the trending topics within the Indian context. The chart displays trending research topics in precision agriculture within India. Recent focus areas include deep learning, machine learning, and convolutional neural networks, indicating a shift toward AI-driven approaches. Larger bubbles show higher term frequency, with deep learning emerging as the most dominant theme. While global research in precision agriculture adopts advanced technologies such as IoT, ML, and DL, the Indian context reflects a dual focus: addressing irrigation management, soil moisture monitoring, and crop yield optimization while gradually incorporating these cutting-edge technologies. The network analysis shown in Figure 22 highlights that Indian research also follows the global trend of high-tech, resource-intensive solutions. Citation analysis reveals a growing influence of Indian research, with key publications addressing region-specific issues. Trend analysis reveals that while global research encompasses automation, robotics, and AI-driven innovations, Indian studies focus on practical applications that address immediate agricultural challenges, reflecting the socio-economic and environmental contexts of the region. This comparative approach underlines the unique contributions of Indian research while highlighting areas for potential alignment with global advancements.

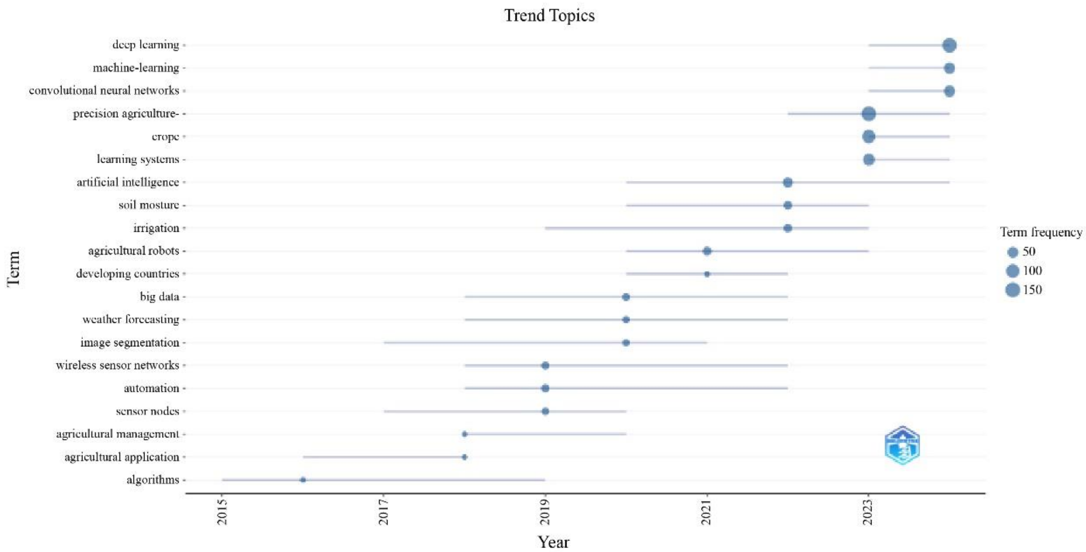

Fig. 21 Trend topics - India

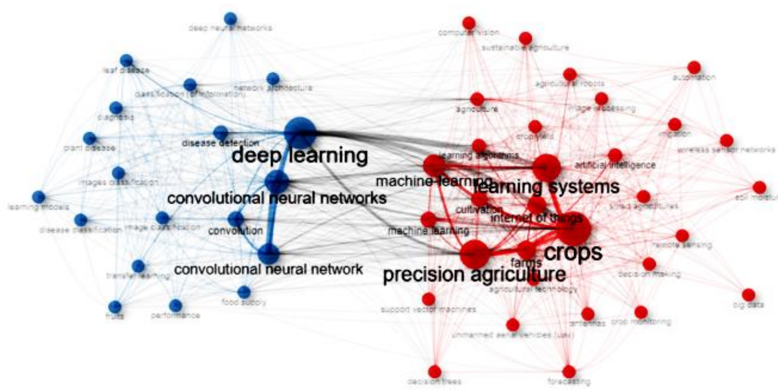

Fig. 22 Co-occurrence analysis – India

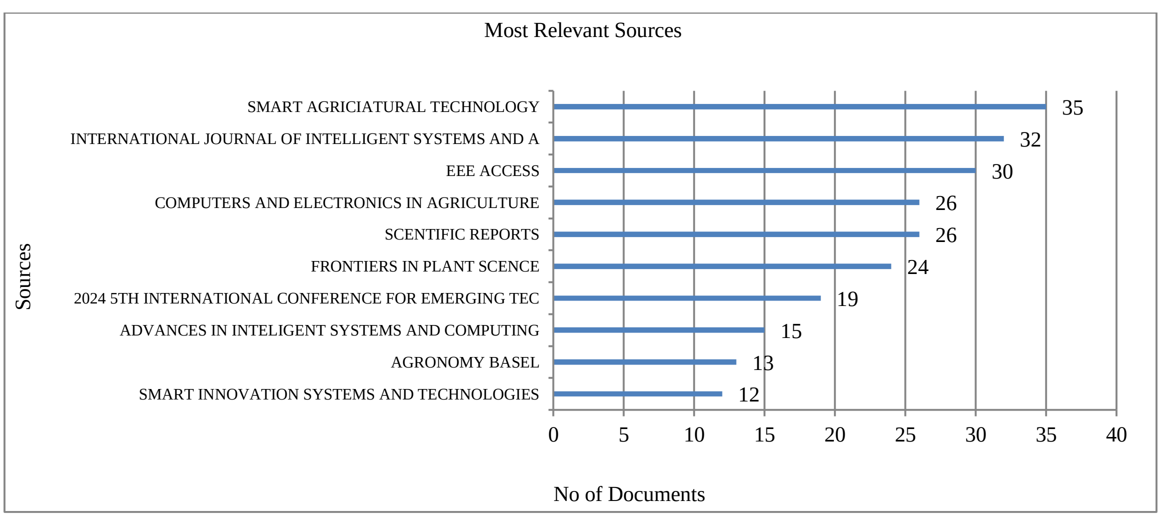

Fig. 23 Most relevant sources – India

Figure 23 shows the most relevant sources from the Indian context. The graph displays the most relevant publication sources for research in precision agriculture. "Smart Agricultural Technology" leads with the highest number of documents, followed by journals like "International Journal of Intelligent Systems and Applications" and "IEEE Access." The bubble size indicates the volume of publications per source. This highlights where the most impactful and frequent research is being published in the domain.

5. Discussion

Bibliometric analyses in precision agriculture offer significant comprehension of development and progress [50, 51]. This study [52] guides researchers and practitioners in utilizing deep learning in agriculture. This study [53] uses bibliometric analysis with VOSviewer to map the author network in precision agriculture, revealing key collaboration patterns and offering insights for enhancing research partnerships and advancing sustainable agricultural innovations.

This study builds on existing research by providing valuable insights into key areas, including integrating emerging technologies, a holistic evaluation of Sustainability, and regional and contextual variations. It expands the understanding of how advanced tools and methods work together to enhance smart farming, examines Sustainability from economic, environmental, and social perspectives, and highlights the importance of tailoring approaches to the distinctive needs of different areas and farming systems.

5.1. Predominant Research Themes in Smart Farming

The core themes in smart farming encompass advanced technologies such as ML, DL, agricultural robotics, and deep learning. These technologies collectively drive innovation and efficiency in modern agriculture. Key applications include crop yield prediction, crop recommendation systems, fertilizer optimization, weed management, pesticide application, and soil management. These associated techniques aim to enhance productivity, ensure sustainable resource utilization, and support informed decision-making processes in agricultural practices. By incorporating these technologies, smart farming enables precision agriculture, transforming traditional farming into a more efficient and environmentally friendly approach.

Machine learning involves creating programs based on input data and corresponding outputs, making it ideal for building predictive models. Various ML methods have recently been applied in agriculture to enhance crop yields, classify soil types, and perform other applications. Integrating data from sensors converts agricultural management platforms into real-time, AI-driven solutions, providing farmers with actionable insights and recommendations for better decision-making [54]. A mobile system powered by machine learning that uses ML algorithms can help optimize farmland and monitor crops. This app provides farmers with valuable land information to support better decision-making. Machine learning models for setting parameters should be integrated directly into mobile applications for seamless use [55]. A machine learning-driven automation approach for agriculture has been proposed [56], suggesting that ensemble learning can effectively fine-tune parameters. Additionally, a mobile application could support farmers by providing valuable insights and guidance throughout the farming process, from seed sowing to crop production.

This study [57] presents a framework using Naive Bayes classification to recommend optimal crops for farmers in Tumakuru, Karnataka, leveraging machine learning and the IoT to enhance agricultural productivity and economic growth. This study evaluates the effectiveness of two PCA-based methods, NIPALS and EM, in imputing missing values within high-dimensional agro-meteorological datasets, specifically focusing on reference Evapotranspiration (ETo). The study analyzed meteorological data from 45 weather observatories in São Paulo, Brazil, from 2011 to 2021, simulating five degrees of missing data (10% to 50%) to assess the effectiveness of these strategies [58]. There is a growing need to integrate these individual approaches to achieve better automation in precision agriculture. Table 5 shows analyses of ML regarding its capabilities and limitations.

Table 5. Capabilities of ML techniques in precision agriculture

Strengths	Weaknesses
ML can integrate and handle heterogeneous data sources such as images, sensor outputs, weather data, and textual inputs, which is essential in precision agriculture [59].	The effectiveness of models depends heavily on data quality; noise or bias in data can lead to incorrect predictions or decisions. It requires filtering of low-quality and misleading data [60]
It allows flexibility in discovering hidden patterns and relationships from data without being constrained by prior assumptions or models [61].	It needs extensive data transformation and aggregation - Preprocessing steps like normalization, feature engineering, and integration of diverse datasets can be time-consuming and complex [62]
Effectively captures intricate relationships among variables (e.g., soil health, crop yield, climate factors), improving prediction accuracy.	Lacks a guiding theory for direct application -Since models often rely solely on data, they may lack explainability or theoretical grounding, which can hinder trust and understanding among domain experts.
Enables data-driven decisions designed for specific fields, crops, or	Computationally intensive training with significant time demands -Training complex

even individual plants, enhancing productivity and resource use efficiency [63, 64]	models like deep learning can require high-performance computing resources and long training times, which may not be feasible in all agricultural settings.

Robots and artificial intelligence have been integrated into automated production processes as part of Industry 4.0, and robotic applications powered by AI are essential in producing high-quality, efficient products in competitive industrial nations [65]. The review analyzed 25 studies using computer vision in disease detection, grain quality assessment, and plant phenotyping. It highlighted opportunities to utilize GPU hardware and advanced AI techniques, focusing on applications for major grain crops [42]. The study [66] explored the practical applications of AI and IoT in farms, including innovative machinery, irrigation systems, pest management, greenhouse cultivation, and crop health monitoring. It highlights the transition of these technologies from concept to implementation, addressing their technical aspects and adoption challenges. AI applications in irrigation, weeding, and spraying enhance resource efficiency, improve soil health, increase labor productivity, and improve the quality of agricultural output [67]. A study on maize yield prediction in Nigeria identified Stochastic Gradient Descent (SGD) as the most effective algorithm, achieving a high R^2 score of 0.985. The Python-based system aids farmers and industries in decision-making and resource planning [68].

This work integrates DL, IoT, and digital technologies in smart agriculture, showing that deep learning outperforms traditional methods in accuracy. It also proposes web-crawling bots for gathering crop data, offering valuable insights for researchers to apply deep learning to agricultural challenges [69]. This paper [70] presents a crop disease prediction model utilizing deep convolutional neural networks that can be used on a mobile phone. The dCrop app, which can identify 38 crop diseases with high accuracy, operates offline, making it accessible to farmers worldwide. Future enhancements could include support for regional languages and recommendations for pesticides or fertilizers tailored to the identified diseases. Machine learning-driven machinery enhances farming efficiency and crop quality, while advanced systems detect diseases, reduce pesticide use, and transform the agricultural industry [70]. This study presents a DL-based approach using the IoT to assist decision-making in smart farming. Utilizing the LSTM algorithm, the system outperforms other classification methods, providing intelligent prediction and control for greenhouse plants [72]. Precision agriculture minimizes direct farmer involvement by utilizing IoT systems to monitor and control soil properties, crop yield, and temperature. Sensors collect data transmitted to an IoT cloud for remote observation and analysis. This aids in duties such as animal intrusion detection and crop projections. The IoT also serves as a data storage technology, enabling more informed decision-making and improved forecasting for agricultural production [73, 74]. This study introduces a CNNIR-OWELM technique for early detection and categorising rice plant maladies in smart farming, utilizing IoT devices for image capture and cloud transmission. To increase classification accuracy, the model integrates histogram segmentation, a deep learning-based foundation using ResNet v2, and an optimized WELM (OWELM) with the Flower Pollination Algorithm (FPA), outperforming previous models [75].

A simplified weed identification model based on an upgraded YOLOv8s network was developed to address the challenges of high computational demands and deployment in maize fields. Key features include the newly designed D-PP-HGNet, AFAM, and Global Max Pooling, which aim to enhance feature extraction. The model's performance improved significantly, with accuracy increasing from 91.2% to 95.8%, recall rising from 87.9% to 93.2%, and mAP@0.5 improving from 90.8% to 94.5%.

This improved model beat current discovery models, including YOLOv5s and YOLOv8l Faster R-CNN, delivering higher accuracy and efficiency, making it ideal for weed identification in resource-constrained applications [76]. AgroTec 4.0 [77], a smart farming system that integrates edge computing, has improved strawberry cultivation in Ecuador's Andean region, boosting yields by 15%, reducing water usage by 20%, and enhancing fruit quality with a higher Brix index and increased weight. The system also delivered significant economic benefits, achieving a 103% ROI for small-scale producers. CNNs are often used in agricultural research due to their outstanding image-processing capabilities. Deep learning applications are commonly used for plant and crop classification.

Table 6. Notable domains used in smart farming studies

Domain	Deep Learning Implementation
Diseases	Wheat disease diagnostic procedures are among the methods for plant-specific identification of diseases. [78], A DL-powered sensor designed to detect tomato illnesses and pests [86] and identify disorders in tea leaves. [79].
Plant Classification	Deep CNN is applied for sorting of haloid maize seeds [80]
Pest Recognition	Deep learning methods for classifying moth images [81]
Weed Detection	Learning approach employing CNN for weed detection [82]
Land Cover Identification	A method for creating sustainable goal indicators assessment using high-resolution satellite data [83]

Still, they also play a crucial role in predicting soil moisture, estimating yields, classifying leaves, detecting diseases, and identifying plants. The Table 6 highlights how deep learning techniques are applied across bright farming areas.

5.2. Crops Studied in Smart Farming

This section highlights the most extensively explored crops in data science models, focusing on four key elements of crop management: yield forecasting, disease identification, crop recognition, and crop quality. A total of 634 papers related to crop species were examined. Maize (corn) ranks first due to its widespread cultivation and diverse applications, including human consumption, animal feed, and biofuel production. Wheat and rice follow, with wheat being the most widely traded crop globally and rice being the most prominent in Asia. Soybeans, widely cultivated in the USA, East Asia, Africa, and Australia, are also frequently studied. Other notable crops include cotton, sugarcane, and barley, which are widely cultivated and researched. Table 7 lists the notable crops used in the study and their intended purposes.

Table 7. Notable crops studied in the literature

Crop	Purpose
Maize (Corn)	Early detection of plant diseases minimizes crop losses [84]. Forecasting Maize Downy Mildew (MDM) [85] A multi-temporal model, leveraging machine learning and critical maize density features, achieved enhanced estimation accuracy (R^2 = 0.602, RMSE = 0.094) during key growth stages, such as leaf development, stem elongation, and tasselling [86]. Identifying Infected Maize Crop Using Leaf Images [87] Predicting Maize Biomass Yield [88] Yield Prediction [89]
Wheat	prediction of crop yields [90] UAVs in agriculture showcasing automated ear counting as a scalable solution for accurate yield prediction and improved sustainability [91] The Average Fertilizer Production Score established the optimal nitrogen application rate. [92]
Rice	Fertilizer Optimization [93] rice production [94] rice cropped using subsurface drip irrigation [95]

5.3. Research Directions

The primary purpose of smart farming is to enhance agricultural output while minimizing resource consumption, thereby increasing farmers' return on investment. India's growing interest in smart farming and precision agriculture reflects global influence and local necessity. While the deployment of technologies such as AI, IoT, and deep learning has gained momentum, the Indian context presents unique challenges that must be addressed to ensure the sustainable adoption of these technologies. This analysis presents emerging themes, critical gaps, and forward-looking strategies across technological and research dimensions.

5.3.1. Data Management and Standardization

A recurring challenge in India's precision agriculture ecosystem is the collection, cleaning, integration, and secure sharing of agricultural data. Given the diverse sources and formats, ranging from sensor outputs and satellite imagery to manual inputs from farmers, data heterogeneity severely restricts the development of reliable predictive systems. Region-specific variances further compound the issue, making standardization a necessary yet underdeveloped area [96].

AI and ML models' success relies heavily on the availability of high-quality, integrated datasets. However, fragmented and inconsistently formatted data and limited interoperability across systems hinder model training and cross-comparative analyses. This restricts the scalability of solutions from pilot stages to broader, real-world deployments [97]. Future strategies must prioritize the creation of open, standardized data platforms that support region-specific annotation integration across stakeholders, including government, private, farmer-level, and real-time accessibility.

5.3.2. The Practical Edge of AI, ML, and DL Technologies

AI, ML, and DL hold great promise for optimizing agricultural processes, including crop monitoring, yield prediction, resource optimization, and disease detection [98]. Their ability to replace intuition-driven decisions with data-driven insights is a critical advancement, especially in a country where traditional farming still dominates. Implementing AI is essential to optimize cultivation processes and establish a conducive environment for agricultural markets [68].

Despite this, the deployment of AI/ML in India remains limited due to poor infrastructure, insufficient access to computing power, and a lack of localized models. Furthermore, the large-scale training of these models requires data and computational resources, such as high-capacity servers and cloud systems, which are often unavailable to smaller institutions or remote areas. Investment in cloud-based and edge computing infrastructure, combined with lightweight AI models designed for low-resource environments, will be critical to unlocking the potential of these technologies in Indian agriculture.

5.3.3. Cybersecurity and IoT Vulnerabilities

As Indian farms become increasingly digitized and connected through IoT, they also become vulnerable to cyber threats, particularly malware propagation across devices [99]. Given the limited technical expertise of end users (i.e., farmers), detecting and mitigating such threats pose serious concerns for operational stability and data integrity. Security must be embedded in the design of agricultural IoT systems. This includes user-friendly malware detection frameworks, lightweight antivirus protocols for embedded devices, and farmer education on basic digital hygiene.

5.3.4. Technological Trends

Future trends suggest utilizing swarm intelligence to enhance AI and IoT applications in precision agriculture [100]. Adaptive algorithms, such as SVM-PSO and ANN-GWO, can enhance forecasting in diverse ecosystems. UAV swarms equipped with cameras and computer vision can enable real-time field monitoring, automated pesticide spraying, and irrigation management. Mobile robots can automate harvesting and weed control tasks, while meta-heuristic algorithms can optimize sensor deployment [101].

Offline chatbots can support farmers in areas with limited connectivity, providing expert advice and solutions. AI-driven renewable energy plants could further reduce operational costs and enhance Sustainability in agriculture [102]. Adopting these trends requires multi-sectoral collaboration among agronomists, AI engineers, policymakers, and local communities. R&D must focus on cost-effective technologies custom-made for Indian agro-climatic zones.

5.3.5. Strategic Outlook

Despite technological advancements, the adoption of precision agriculture in India remains limited. Key challenges such as fragmented data, low levels of digital literacy, inconsistent infrastructure, and cybersecurity risks need to be addressed through inclusive, policy-driven innovation. While the global Agriculture 4.0 model offers valuable insights, its successful application in India requires careful adaptation to the local socio-economic context. Building agro-tech capacity among farmers and field officers is essential, as is integrating renewable energy and automation to promote sustainable farming practices. To improve precision agriculture in India, some clear policy steps are needed.

Creating a national agriculture data system is important. This means building open, standardized platforms that allow real-time, location-based data sharing among different groups. Funding research on simple, flexible AI models that work in rural areas should also support local AI solutions. These tools should be designed with help from farmers so they are easy to use and meet real needs. Digital safety is another big concern-basic cybersecurity rules should be required for farming devices, and farmers should be taught how to stay safe online.

Research in this field also needs a better structure. National datasets and shared methods to test AI tools can help researchers compare results and build stronger solutions. Finally, supporting small companies and research teams in creating affordable offline tools is important. Smart farming tools should also include clean energy options to make farming more sustainable.

5.3.6. Methodological Gaps

A significant methodological weakness across many studies is the absence of comparative AI and data science techniques analyses. Without rigorous side-by-side evaluations, it is difficult to determine which models or algorithms are most effective under specific agricultural conditions.

Moreover, many studies do not employ standardized evaluation metrics or benchmarking datasets, leading to challenges in reproducibility and validation. This hinders accumulating a cohesive body of knowledge and restricts the ability to build upon previous work systematically.

The field urgently needs methodological consistency through the establishment of benchmark datasets, cross-validation strategies, and standard performance indicators. These would enhance the scientific validity of findings and facilitate model transferability across regions and crops.

5.3.7. Future Research Directions

There is a growing need to move beyond purely applied technological approaches in smart farming and instead develop unified theoretical frameworks that integrate AI, agronomy, decision sciences, and behavioral economics. Such interdisciplinary integration would provide a more comprehensive understanding of how smart farming technologies interact with environmental systems and human decision-making.

To achieve this, collaboration between technical experts and agricultural domain specialists is essential, as it encourages the development of context-aware models and decision-support systems.

In addition to theoretical advancements, methodological innovations are critical for ensuring the reliability and applicability of predictive models. Robust cross-validation techniques and standardized benchmarking protocols are necessary to evaluate not only traditional metrics, such as accuracy or F1-score, but also practical outcomes, including yield enhancement, resource efficiency, and environmental Sustainability.

Open-access datasets and collaborative research platforms should be established to facilitate reproducibility and thorough testing of AI models in real-world farming conditions. Future solutions must prioritize lightweight and modular AI architectures that can function on mobile devices or offline settings. Involving farmers and agricultural extension agents in the design process is vital to ensure usability, adaptability, and successful adoption across diverse agro-climatic and socio-economic contexts.

5.3.8. Implications for Future Research

Although smart farming has made progress, considerable research gaps still exist in the application of data science-based automation in Indian agriculture. These gaps can be summarized as follows.

1) Existing research lacks region-specific models addressing varied climatic and soil conditions. Existing crop advisory systems do not incorporate multi-source agricultural data, which reduces their accuracy.

2) Yield forecasting models are imprecise because data collection is not uniform, and farm-level variables are missing.

3) There is also a deficit in real-time, automated crop monitoring technology, which makes pest management, weed control, and disease identification primarily manual.

4) Furthermore, fertilizer strategies remain suboptimal and often promote the inefficient use of resources.

5) Furthermore, constraints such as technology adoption, cost, digital skills, and connectivity hinder large-scale deployment.

Filling these gaps requires a comprehensive, scalable, and farmer-centric innovative farming platform that leverages Machine Learning, Deep Learning, and Computer Vision for improved crop management, informed decision-making, and enhanced automation.

By addressing these research gaps, future studies can contribute to a more robust and impactful integration of data science in smart farming, ensuring Sustainability and efficiency across diverse agricultural landscapes.

6. Proposed System

Farming systems are complex and dynamic, comprising numerous interconnected subsystems that involve various stakeholders with different roles and expectations.

These systems rely on vital data about natural resources and external processes.

Data flows across the supply chain, from suppliers and producers to processors, traders, and consumers, and plays a key role in enabling data science and automation in smart farming. The study employs a design-based approach, utilizing an information-based management cycle for farming. Crops are shortlisted based on lifecycle duration, categorized as short-term or long-term, and initially tested on short-term crops.

The data science process is customized for crop management, involving six key steps: defining research goals to optimize crop production, collecting and storing large datasets from heterogeneous sources on a Big Data platform, preparing data through pre-processing techniques, exploring data to uncover patterns and anomalies, building and validating predictive models using machine learning and statistical methods, and finally presenting results and automating processes for improved decision-making.

This iterative, prototype-driven approach can be adapted for other crops in similar categories, enabling scalable and efficient solutions. A general approach has been proposed to achieve the desired goal.

The design process includes 1) defining and identifying the problem, 2) designing a framework, 3) testing the framework, and 4) automating and applying the framework.

This process will be repeated for each problem, and the resulting frameworks will be integrated to build the final system. The overall system design integrates all processes to provide an optimal solution for efficient farming.

The system identifies data types, collects data from various sources, stores and processes it using Big Data systems, and performs data analysis and decision generation.

These functions are applied to each objective and various plant inputs. Figure 24 outlines the approach taken to design the framework, while Figure 25 illustrates the complete system design.

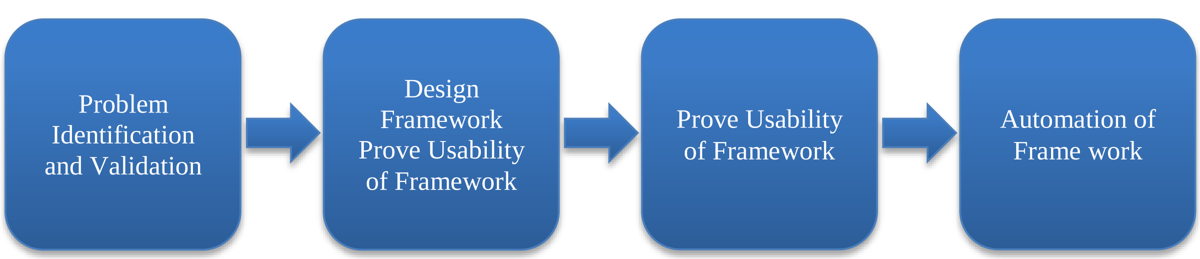

Fig. 24 Design cycle

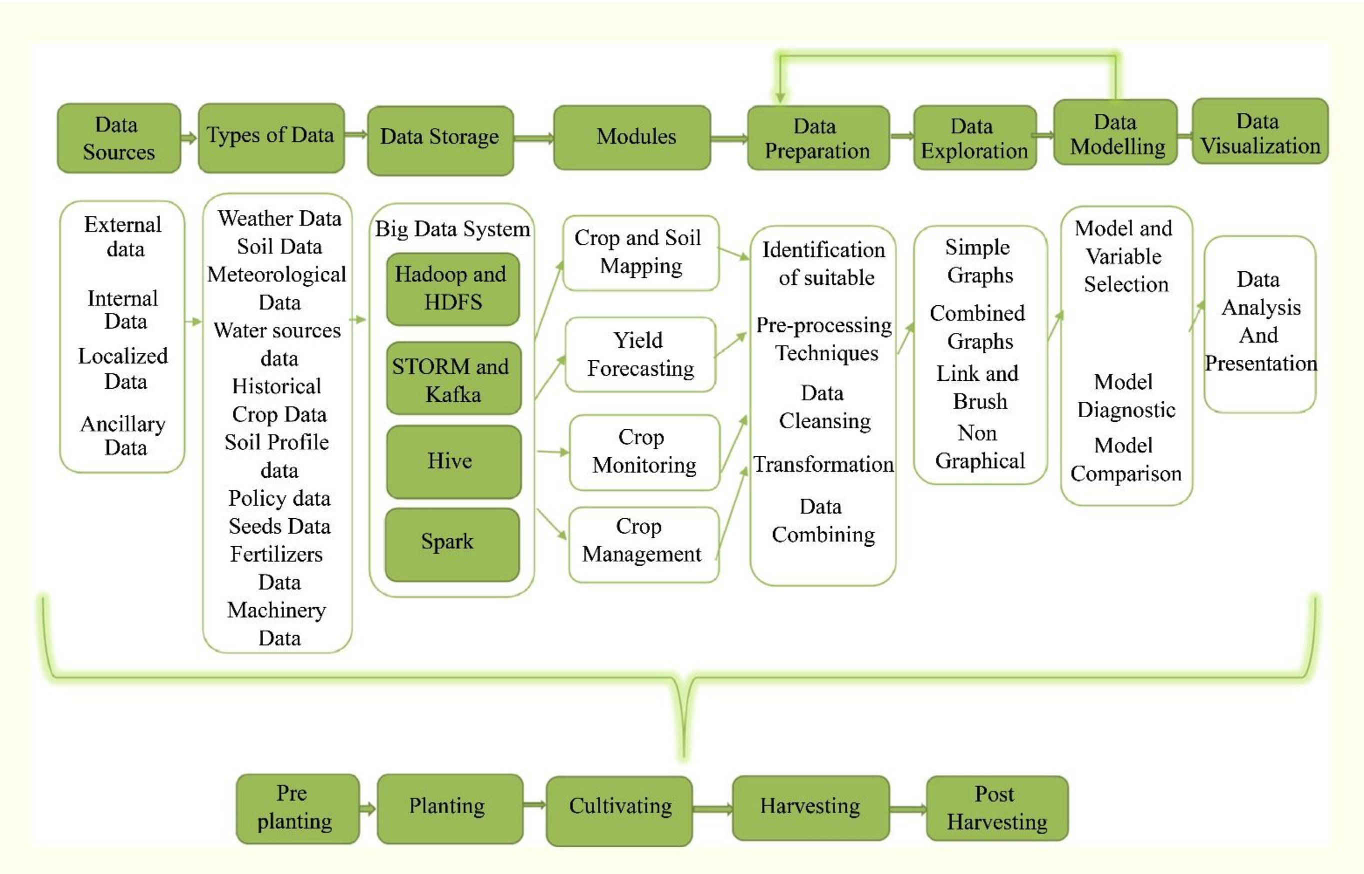

Fig. 25 Proposed system architecture

7. Conclusion

Data science in smart farming has the potential to transform traditional agricultural processes by increasing crop yields and improving farm management. For Indian farmers, these techniques can support informed decision-making and better resource utilization. Bibliometric analyses reveal that India, the United States, China, and Brazil are the most active nations in this research area. Key focus topics include plant diseases, soil management and analysis, crop yield prediction, crop recommendation and fertilizer optimization. However, applying DL algorithms in precision farming presents significant challenges, addressing which can advance the field and promote its adoption among stakeholders. This study proposes an integrated system framework that automates data across every stage of the crop management lifecycle. The framework is adaptable to various crops, focusing on accurate crop yield forecasting and prediction. The system aims to provide an efficient, resource-optimized solution to enhance agricultural productivity.

7.1. Future Work

The suggested system architecture provides a solid basis for practical farming; nevertheless, more improvements are required for greater application and scalability. Future studies will focus on expanding the system to accept larger datasets and more diversified agricultural techniques, making it ideal for huge farming regions. The utilization of IoT devices for gathering data in real-time, including moisture in the soil and temperature, besides insect detection, improves decision accuracy. Advanced ML and DL algorithms will be developed to increase prediction accuracy and automate decision-making processes. Customization for various crops and locales will include regional agronomic approaches and environmental considerations.

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