Thematic Evolution and Global Trends in IoT- and AI-Based Precision Agriculture

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Abstract – This systematic review examines the development, thematic emphasis, and international contributions of IoT- and AI-based precision agriculture studies between 2015 and 2024. Approximately 200 publications were obtained following a critical search in the Scopus, IEEE, ACM, ScienceDirect, and Google Scholar databases. Metadata, the type of publication, the source and the country affiliation of the authors were extracted and interpreted. Our quantitative synthesis showed growing trends in publication with IEEE and Scopus dominating as sources. Thematic analysis supplied 6 main clusters, namely, smart irrigation systems, soil and crop monitoring, predictive yield analytics, pest and disease detection, climate-smart agricultural practices, and data-driven decision support systems. India, China, Taiwan, and the USA became leading contributors, which demonstrates that the field captured a wide interest globally. The results reveal the increasing incorporation of sensor technologies and AI models in improving productivity, sustainability, and decision-making in agriculture.

Keywords – IoT, Artificial Intelligence, Precision Agriculture, Smart Irrigation, Predictive Yield Analytics, Sensor-Based Monitoring, Global Research Trends.

I. INTRODUCTION

With the world now being far more complex and more interconnected, companies are now resorting to the concept of using data to make decisions to bypass the uncertainty and improve their competitiveness in the world. This way of doing things has taken advantage of the rich information available in many sources in such a manner that the executives can apply it and make prudent decisions that will see them and their plans compatible. Elaborate models of analysis and instrumentation enable a company to identify patterns or trends and anticipate outcomes.

The rise of big data technology has ensured that information can now be recorded and processed in a manner never witnessed before. Businesses can apply analytics to facilitate real-time decisions. In a case where the decisions are supported by the information they have, they create an environment in which the behaviors can be easily traced and followed. This implies that the stakeholders will be able to base their decisions on evidence rather than feeling, opinion or guess. This will definitely create a culture of accountability and transparency. Nevertheless, it is necessary not only to get familiar with technology but also to transform the organizational culture [1].

Increasing issues in modern agriculture include climate change, population, and increasing demands to utilize few resources to produce more food. Consequently, the current agricultural practices have become focused on evidence-based decision making. Data can inform farmers to make important decisions about production in order to have more efficient, less impactful, safer, and sustainable harvests. Evidence-based decision-making is transforming farming into a better way, producing more with less and solving the global food security problem. The advantages are evident, in spite of the issues and difficulties that should be addressed. As the level of technological improvement advances, data-driven agriculture will become more accessible and effective as the future of world farming [2]. This digital change is meaningful to ensure sustainable and food-secure future. Agriculture based on data seems to be the future despite numerous challenges.

Precision agriculture has emerged as a game-changing strategy in agriculture, offering customers more efficient, productive and sustainable solutions to agriculture's growing problems. Precision Agriculture is essentially using technology to observe, measure and analyze the variability in the field for better decision making by the farmers and to improve yield and reduce waste. Farmers may use technology like satellite images, GPS, and IoT devices to keep track of environmental components, soil properties, and crops in real-time for more precise actions [3]. Through ML, big data analytics and AI, farm mechanization, automated cropping equipment and other such technologies get better with time.

IoT sensors allow for real-time monitoring of soil moisture, fertilizer level, temperature, etc. AI and ML systems borrow from a dataset to produce actionable and predictive insights from the data see **Fig. 1** Farmers can ensure the profitability of their enterprise by effectively utilizing cloud services which allows easy access, faster storage, and rapid processing of large volumes of big data. With the advancement of precision agriculture, technology is improving and there is a recognition that it requires an increasingly sustainable and efficient approach. As these technologies advance, PA will increasingly allow for large-scale changes in agricultural practices and address global agricultural challenges.

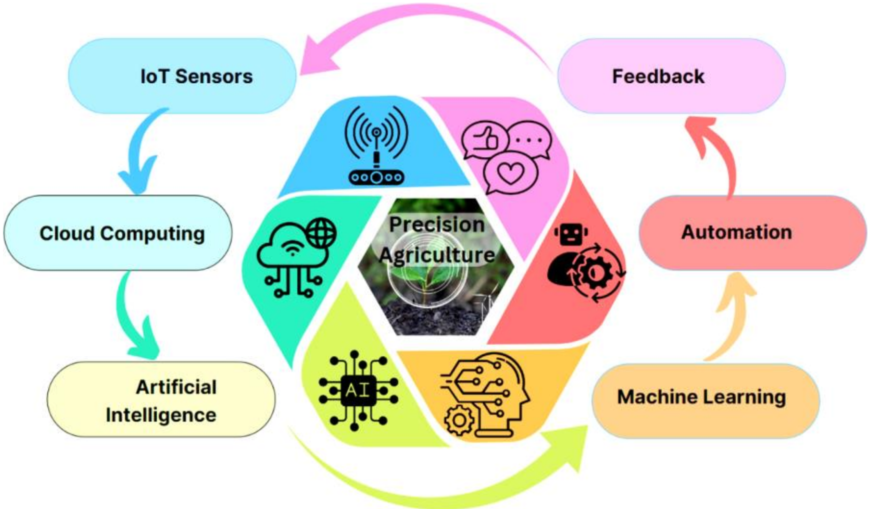

Fig 1. Precision Agriculture Components.

These technologies help in predictive modeling, which allows farmers to forecast yields, optimize planting and respond smarter to pests, disease, and bad weather. Furthermore, drones and driverless vehicles are now being used in the management of agriculture to provide precision spraying, robotic harvesting and better monitoring of large-scale farming. These revolutions can improve farm production, and lessen the excessive use of things like pesticides, fertilizers, and water, so they help make farming more sustainable by lessening its impact on the environment [5].

This paper systematically attempts to evaluate the publishing trend, global contributions, and thematic clusters of all studies on the AI- and IoT-driven Precision Farming in the last 10 years. Through the synthesis of metadata, the types of publication, source, and research foci, the paper will capture a deeper understanding of the conceptual and technological trajectories in precision agriculture as well as clarify the gaps and prospects of future research [4].

The remaining sections of this study have been organized in the following manner: Section II describes enabling technology for PA. These technologies include, but not limited to, remote sensing technologies, IoT sensors, ML/AI in agriculture, and FMIS. Section III describes the process of collecting data, quantitative synthesis, and thematic categorization. In Section IV, a detailed account of our results has been provided to further provide more insights into (i) publication distribution and global contributions, and (ii) comparative characteristics and thematic insights. Lastly, Section V concludes the study and highlights the application of AI- and IoT-based PA in enhancing accuracy and real-time data streaming.

II. ENABLING TECHNOLOGIES FOR PRECISION AGRICULTURE

Remote Sensing Technologies

Remote sensing frameworks employed for agriculture and PA widely can be grouped based on (i) sensor type, (ii) sensor platform. Sensors are typically affixed to terrestrial platforms, aerial vehicles, and satellites see **Fig. 2**. Since the 1970s, satellites products have been widely employed for PA. Recently, aerial systems, including UAVs (unmanned aerial vehicles), and airplanes, have been employed in public administration.

Notes: Soil Moisture Active Passive (SMAP), Precision Agriculture (PA), Soil Moisture (SM), Unmanned Aerial Vehicle (UAV), and Electromagnetic (EM) are all acronyms. Ripendra Awal of PVAMU in Prairie View, Texas, USA, is credited with taking the UAV image [6].

Ground-oriented systems employed for PA may be classified into three groups: (ii) fee-standing in fields, (ii) hand-held, and (iii) installed on agricultural machines or tractors. These systems are situated in close proximity to the vegetation o target surfaces in contrast to satellite-oriented or aerial systems.

Sensors used in remote sensing vary based on their temporal, radiometric, spectral, and spatial resolutions [7]. The spatial resolution of sensors is founded upon its pixel dimensions, which correspond to the ground field. Sensors having the highest spatial resolution normally have tiny footprints, where those with larger footprints normally have lower spatial resolution. Temporal resolutions are connected to sensors rather than detectors themselves. Temporal resolutions for satellites allude to the time needed to complete a full orbit and return back to its specific observation field.

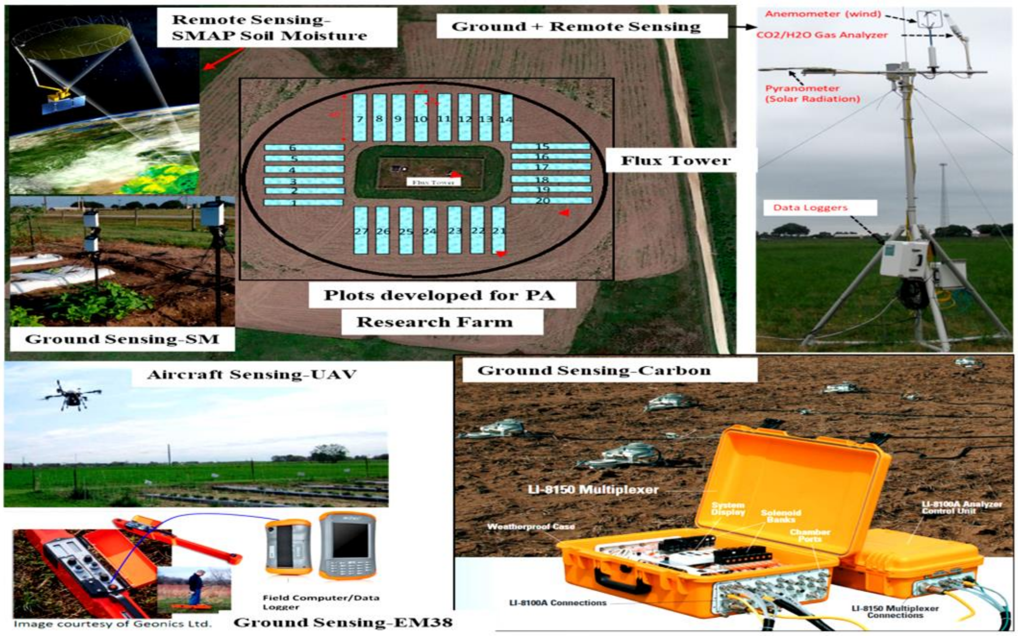

Fig 2. A Standard Configuration for Aerial, Remote, and Terrestrial Sensor Platforms Utilized in PA.

IoT Sensors and Networks

Modern technology is essential for maintaining farms despite limited resources. The application enables farmers to keep track of fluctuations in climate, soil nutrient concentration, water usage, and data management. These days, there's a lot of sensors and computing systems that can gather and manage data from agricultural systems for timely and informed decision-making. Surveillance via video cameras and use of electronic platforms enable farmers to view their farms remotely [8].

Prediction rate decision making in smart farming that is based on models predicting crop yield in environmental conditions expected to be experienced and crop genetic potential. In addition, sophisticated neural networks and simulation models enable reliable decision support for agricultural decisions see **Fig. 3**. As a result of these integrative advancements, farmers can maximize resource usage, minimize waste, and improve the health and productivity of crops. So, it drives a more efficient and sustainable agricultural model [9].

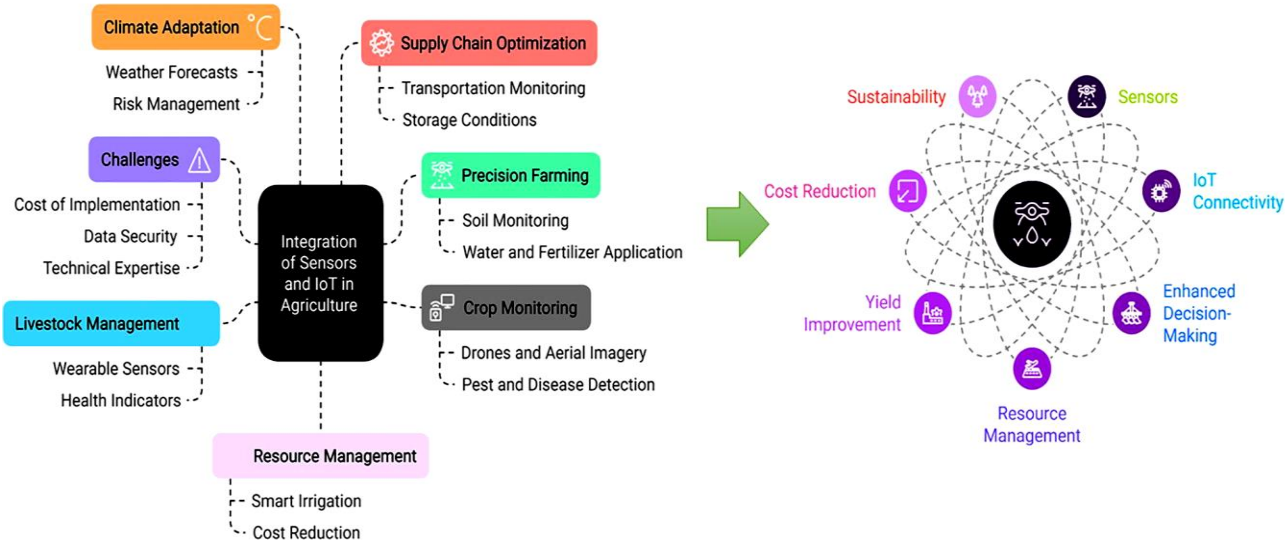

Fig 3. Main Uses of Sensors and IoT in Agriculture.

The efficient use of resources, digitized decision-making, animal surveillance, precision farming, pest and disease management, smart irrigation, greenhouse control and supply chain improvement has been depicted in **Fig. 3**. By using productivity solutions, it is possible to improve agricultural productivity, manage resources sustainably, and enhance agricultural efficiency through sustainability, cost reduction, improvement in yield and management of resources [10].

The IoT-enabled sensors are used to monitor various farming activities in precision agriculture. Multiple sensors present in agricultural fields collect data on the concentrations of nutrients, temperature, pH and moisture in the soil. These sensors provide farmers with real-time information on the condition and needs of various crops [11].

ML and AI in Agriculture

The implementation of AI implies that farmers can use IoT devices to track environmental conditions in real-time and make well-informed decisions to optimize the use of natural resources and produce more crops. IoT gadgets – sensors, drones, and sensing devices – assist in gathering important data (humidity, temperature, moisture, and health status of plants – see **Fig. 4**. The AI systems receive the data in bulk that is then analyzed with the help of ML algorithms to produce results [12].

Precision farming is becoming an essential method for improving yield efficiency. The use of technology involves the creation of apps that can analyze his/her health, call for help and more. Deep learning techniques have enhanced the performance of machine learning, which provides better accuracy in complex problem-solving situations. The rise of automated machine learning (AutoML) makes it possible to construct models, so there will be a reduced reliance on expert data scientists while prediction models can be more stable [13].

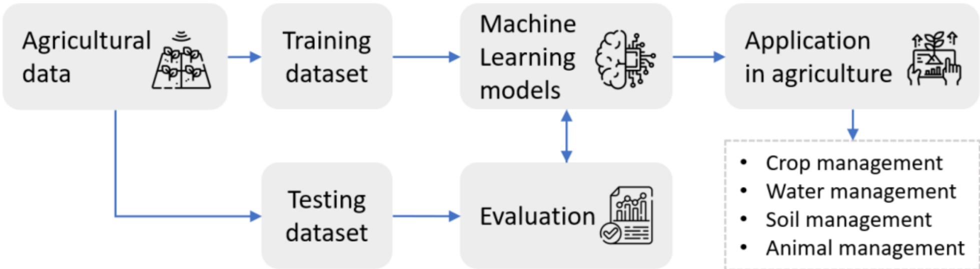

Fig 4. Flowchart of Procedures in ML Model Development and Their Applications

FMIS

FMIS are ICT-based solutions that help farmers and other associated participants in making evidence-based and informed decisions to improve their activities. This publication will focus on value chain players using FMIS to enhance their connection with farmers, and not on farmers using FMIS for farm management see **Fig. 5**.

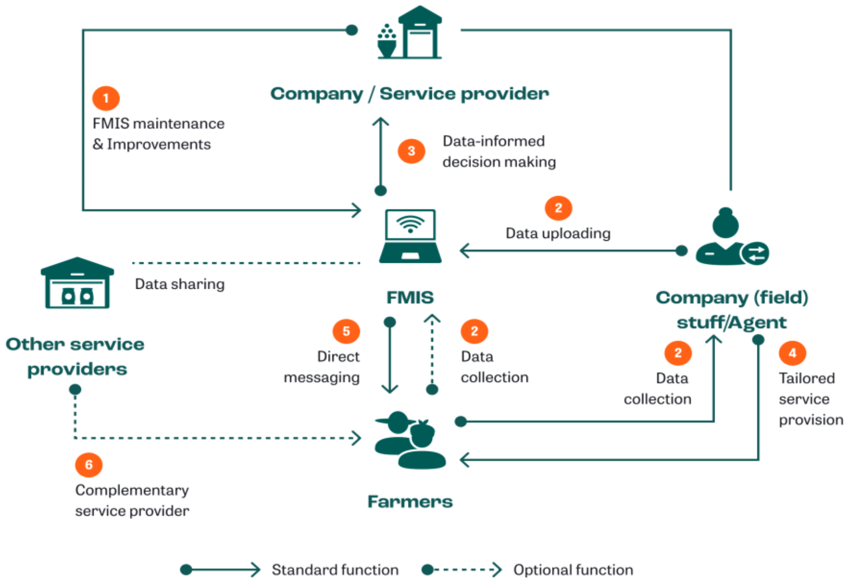

Fig 5. Flowchart on FMIS.

Recently, there has been a rise in the utilization of such systems among associated participants, including agro-industries in low and middle-income countries. They have been demonstrated to facilitate data-driven decisions that bolster smallholder agriculture. Such technologies also facilitate the identification of opportunities to enhance the commercial viability of inclusive business structures [14].

III. DATA EXTRACTION AND ANALYSIS

Data Collection and Coding

It was conducted in a systematic manner to enable methodological rigor, transparency, and reproducibility of the data extraction and coding process. Following the screening stage, the individual publications that met the eligibility criteria were examined to obtain vital metadata, i.e. the title, authorship, and publication year, type of document, source database, and created by the institutions. The other data, including the agricultural focus region (e.g., crop monitoring, irrigation management, soil analysis, yield prediction), the methodology, and the analytical models, was also noted as available. These parameters were summarized into a structured dataset as a way of comparing them among studies.

In order to give the clear overview, **Table 1** summarizes the main features of the included publications, indicating the number of studies per database, type of publication, and location of the studies. By capturing geographical affiliations, it was possible to determine patterns of international collaboration and gain an understanding of regional research capacity in IoT- and AI-based agricultural innovation.

Table 1. Summary of Included Studies by Source, Publication Type, and Region

Source Database	Journal Papers	Conference Papers	Total	Leading Countries Contributing
Scopus	45	18	63	India, China, USA
IEEE	60	35	95	India, USA, Taiwan
ACM	10	8	18	India, China
ScienceDirect	5	7	12	USA, UK
Google Scholar	0	15	15	India, Australia
Total	120	83	203	—

Quantitative Synthesis

A quantitative synthesis to discover statistical patterns and dynamics of research in the corpus was applied. To understand the frequency of publication per year, source, type, and country of origin, descriptive statistics were utilized in the analysis. To demonstrate these trends, visual analytics including bar charts, pie charts, and geographical heat maps have been created. **Table 2** displays the temporal distribution of publications in 2015 through 2024 indicating the trend in the annual research output.

Table 2. Publications by Source Annual Distribution (2015-2024)

Year	Scopus	IEEE	ACM	ScienceDirect	Google Scholar	Total
2015	2	3	1	0	0	6
2016	3	5	0	1	1	10
2017	5	6	2	1	1	15
2018	6	8	2	1	2	19
2019	10	10	3	2	3	28
2020	12	12	3	2	3	32
2021	8	15	2	2	2	29
2022	9	18	3	3	3	36
2023	8	18	2	2	3	33
2024	0	3	0	1	0	4
Total	63	95	18	12	15	203

Table 2 shows that the trend is increasing further, and 2024 publications are already added to the research corpus. Two central distributors in the spread of IoT- and AI-oriented agricultural research are IEEE and Scopus.

Table 3. Other Predominant Research Themes in IoT and AI for Precision Agriculture Archive

Theme	Description	Number of Studies
Smart Irrigation Systems	Use of IoT-enabled sensors and automation for irrigation	45
Soil and Crop Monitoring	Sensor-based monitoring of soil moisture, nutrients, and crop growth	38
Predictive Yield Analytics	AI and ML models predicting crop yields	32
Pest and Disease Detection	AI-assisted detection using imaging and sensor data	27
Climate-Smart Agricultural Practices	Integration of IoT for environmental monitoring and sustainability	22
Data-Driven Decision Support Systems	Decision support platforms combining IoT and AI data streams	39

Thematic Categorization

There was thematic categorization in order to clarify the conceptual and technological focus of included studies. Each publication was analyzed to extract keywords and thematic terms; similar research clusters were identified. **Table 3** summarizes the most common themes which were found throughout the dataset and the counts of representative studies.

The current state of these analyses indicates that in 2024, the research is evolving further towards sensor-based monitoring, predictive models, and integration of AI to optimize agricultural processes. Quantitative and thematic synthesis together provide insights into the publication trends and conceptual orientations, which preconditions Section IV.

IV. RESULTS AND DISCUSSION

This section provides a detailed description of our findings and farming trends identified in literature, addressing the statistical inquiries outlined in **Fig. 6-8**.

Publication Distribution and Global Contributions

The distribution of publications based on sources of retrieval is shown in **Fig. 6**. The review presented in this paper draws data from the five databases that have been examined, namely, ScienceDirect, Google Scholar, IEEE, ACM, and Scopus. No article in this bibliography will be duplicated. Each of them has been credited to their unique source, which includes ScienceDirect, IEEE or ACM. Google Scholar and Scopus extract the papers from several sources such as ScienceDirect, IEEE and ACM.

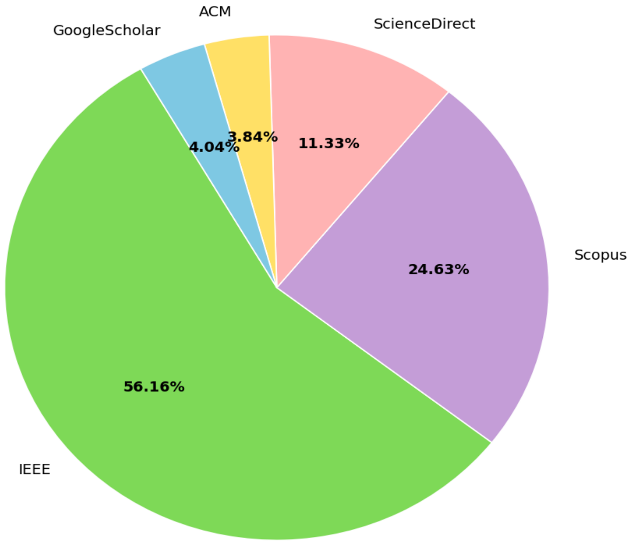

Fig 6. Proportion of Publications Based on Sources.

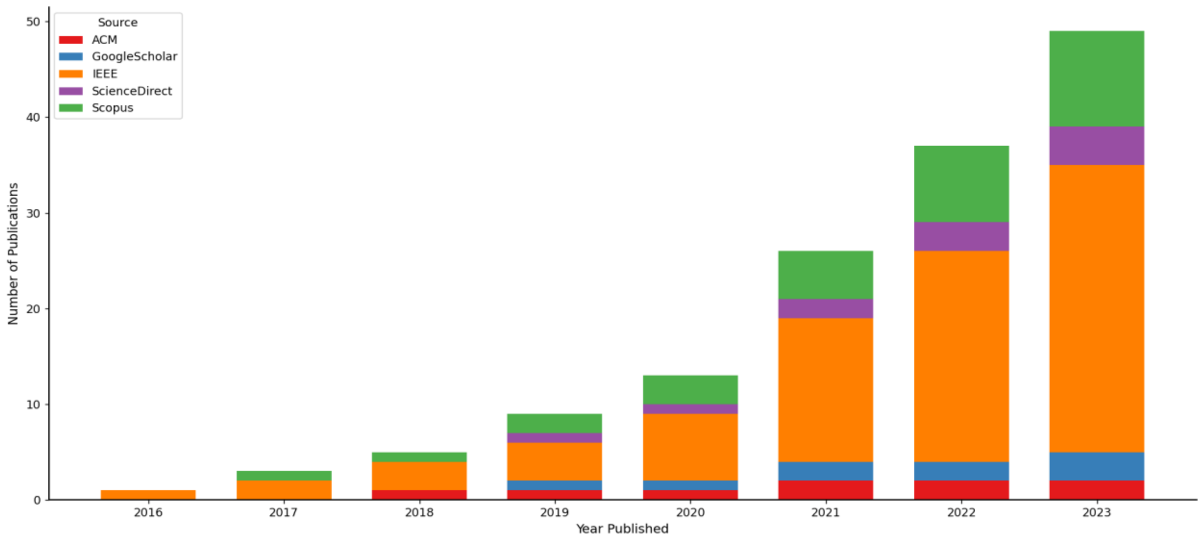

Fig 7. Publication and Source Year of Publication.

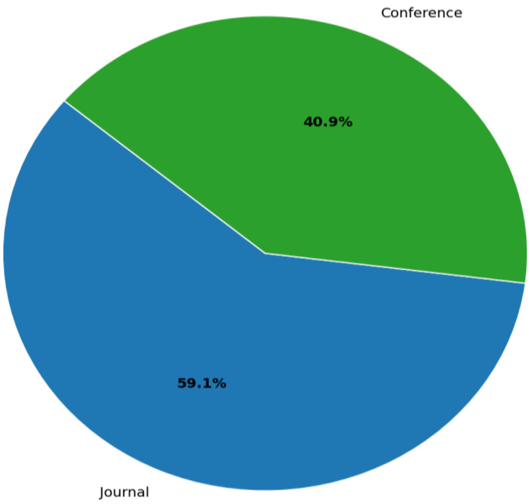

Fig 8. Distribution of Paper in Conferences Proceedings and Journals, By Type of Publication.

Almost a quarter of the found articles were published in Scopus, whereas over 20% were published in IEEE, as illustrated in **Fig. 6**. It is also fascinating to note that less than 25% of the studies were in ACM, Google Scholar and ScienceDirect. An assessment of the journal publication year of all the 203 examined articles reveals an upward pattern in all publications. **Fig. 7** illustrates the yearly publication count of literature papers for every source. Given that the sources were examined before to the conclusion of 2023 and that several conferences and journals may not have yet disseminated their articles publicly online, a consistent increasing trend has been seen throughout.

The distributions of journal articles based on their type is balanced, with journal articles being almost 60% of the total (120 publications) and conference papers around 40% (83 publications). **Fig. 8** illustrates a pie chart depicting the percentage of publications from conferences and journals in response. The authors' institutions originate globally, showcasing the population's variety. The leading four nations in paper contributions are India, China, Taiwan, and the United States [15].

It is noteworthy that eleven nations submitted two papers, while twenty-four countries contributed one paper each. The contribution was deemed to benefit the country collectively when many authors were affiliated with the same institution inside the same nation. Conversely, when the institutions employing the authors are situated in other countries, the counts of each respective country are taken into account [16]. The allocation of articles is graphically shown in **Fig. 9** and **Fig. 10**.

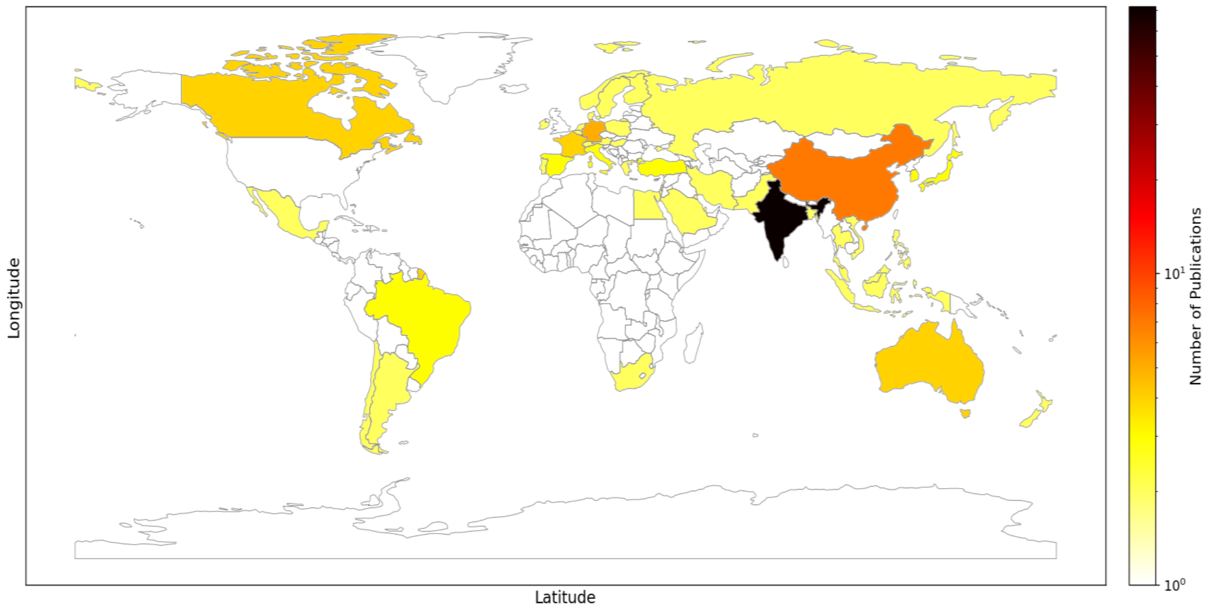

Fig 9. A Geographical Map Illustrating the Number of Publications Per Nation, Showcasing the Worldwide Distribution of Contributions from Authors' Institutions.

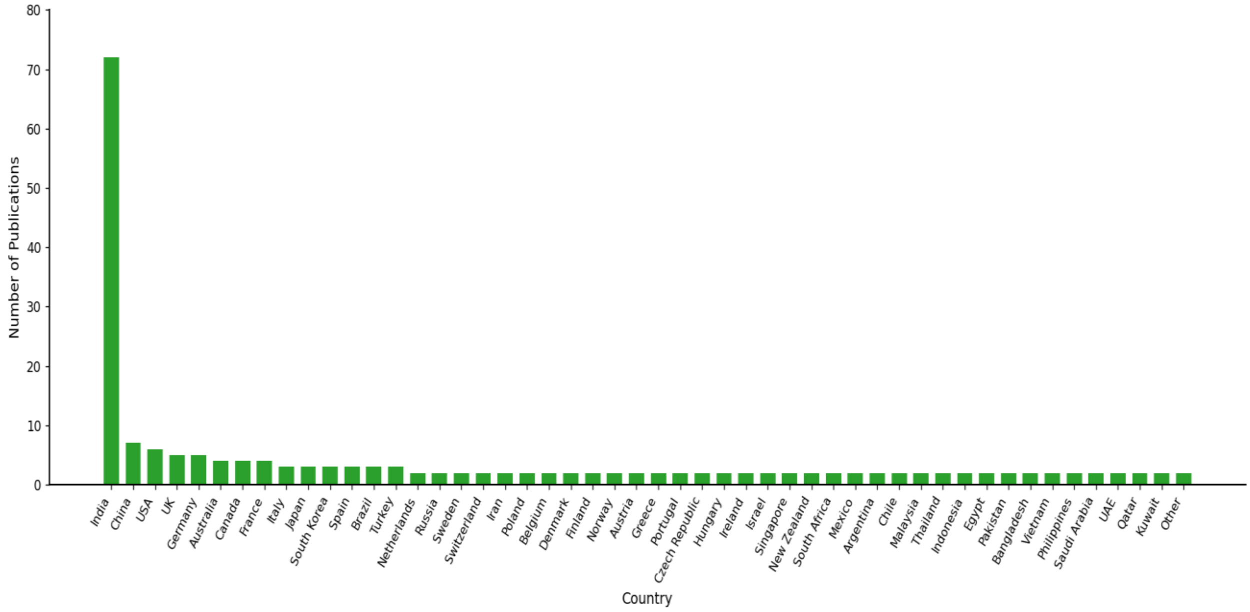

Fig 10. Nations of Institutions That Contribute to the Study of Involved Publications Globally.

Comparative Characteristics and Thematic Insights

The amalgamation of the included studies documented the publication type (conference or journal) and the page count per publication. **Fig. 11** and **Fig. 12** elucidate page distribution across various categories and sources. The page count of publications can serve as an indicator of its overall length; However, it is also worth noting that different conferences or journals have different standards of pages and this affects the amount of information that can be fit on each page.

Fig. 11 shows that journal articles were frequently more than conference publications in all 5 separate sources in terms of the number of pages. The data further reveals that the conference page numbers and their range do not intersect with its journals (without outlier) from all the other sources other than ScienceDirect and Google Scholar). **Fig. 12** indicates that all 5 distinct sources produce a greater number of journals than conferences. **Fig. 13** illustrates the frequent themes and salient subjects identified in the articles studied. This straightforward presentation condenses complicated material into manageable images and acts as a great tool for swiftly understanding major ideas and prominent issues within the research body.

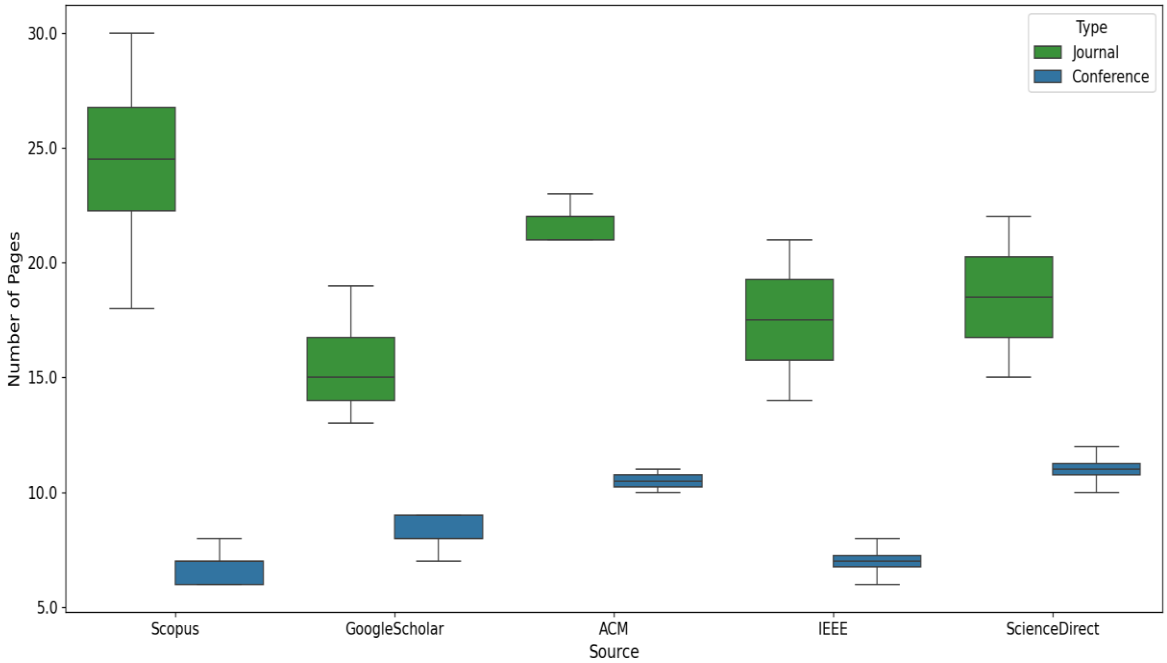

Fig 11. Length of Involved Articles—Perspective of Type and Source.

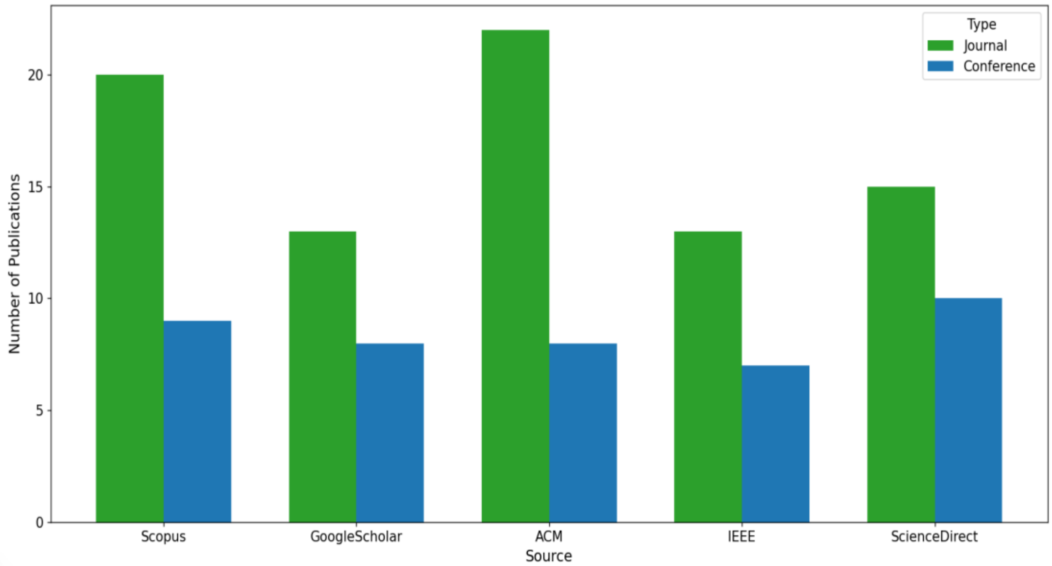

Fig 12. Publications Based on Type and Source.

Fig 13. Keywords Influencing Discourse.

V. CONCLUSION

This systematic review indicates that the field of study anchored on the principles of AI- and IoT-enabled precision agriculture is gradually growing between 2015 and 2024 with India, China, Taiwan, and the USA taking a significant portion. The thematic analysis brings out the superiority of sensor-based monitoring, predictive modelling and decision support systems in the process of improving crop management, efficiency of irrigation and sustainability practices. The findings provide a reasonable insight into the world research, publication preferences, and technological priorities that provide a clear picture of the current state of the situation in the sphere of PA. To add more inclusive and comprehensive development of agricultural innovation, future research should be aimed at adopting modern AI algorithms with real-time data channels, forming cross-country collaborations, and researching underrepresented regions.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

The datasets generated during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Competing Interests
The authors declare no competing interests.

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