PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol x(x): xx–xx
https://doi.org/10.14719/pst.6175

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RESEARCH ARTICLE

A systematic literature review on artificial intelligence in transforming precision agriculture for sustainable farming: Current status and future directions

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OPEN ACCESS

ARTICLE HISTORY

Received: 19 November 2024
Accepted: 03 December 2024

Available online
Version 1.0 : 30 January 2025

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

CITE THIS ARTICLE

Mohammed S P, Deepika J, Sritharan N, Ravichandran V, Prasanthrajan M, Kannan P. A systematic literature review on artificial intelligence in transforming precision agriculture for sustainable farming: Current status and future directions . Plant Science Today (Early Access). https://doi.org/10.14719/pst.6175

Abstract

Agriculture encounters significant challenges, with the demand to increase food production by 50% by 2050 to sustain a growing global population while tackling the impacts of climate change and resource scarcity. Artificial intelligence (AI) has transformative potential for precision agriculture, optimizing crop management, resource allocation and sustainable farming practices. A systematic literature review (SLR) was conducted using the Scopus database, initially identifying 8145 articles. Based on eligibility criteria, 76 were selected for in-depth analysis. This paper focuses on AI applications in key areas of agriculture, including crop monitoring, irrigation management, weed and pest control, yield prediction, and smart spraying technologies. AI-driven techniques, such as machine learning, computer vision, robotics and the Internet of Things (IoT), enhance agricultural productivity and sustainability through data-driven decision-making and real-time monitoring. AI-based irrigation systems optimize water use efficiency by integrating sensor inputs with weather data, while robotic technologies enhance targeted weed and pest management. Resource efficiency is further enhanced by smart sprayers and yield estimation techniques. Despite these advancements, research gaps remain, particularly in integrating AI with emerging fields such as nutrient management and expanding the use of sensor systems. This paper highlights advancements in AI for precision agriculture, including crop monitoring, irrigation management and yield prediction, while identifying gaps in areas like nutrient management and sensor integration. Addressing these gaps is essential for developing more sustainable and resilient agricultural systems.

Keywords

agriculture robots; artificial intelligence; machine learning; systematic literature review; yield prediction

Introduction

Agriculture currently faces significant challenges, including feeding a growing population, coping with climate change and managing limited resources. With the world's population projected to reach nearly 10 billion by 2050, the demand for food will necessitate a 50% increase in agricultural production compared to 2013 levels (1). This increased demand puts immense pressure on agricultural systems to enhance productivity sustainably while minimizing environmental impact. Artificial intelligence (AI) has emerged as a transformative technology capable of addressing these challenges by offering advanced techniques for optimizing crop management, resource allocation, and sustainable farming practices. Leveraging AI in precision agriculture allows for the integration of machine learning, computer vision, robotics, and big data analytics, leading to data-driven decision-making and more efficient farming operations (2,3). AI-driven drones are transforming Indian agriculture through real-time crop monitoring, precision input application, and resource mapping (4). Unmanned aerial vehicles (UAVs) and IoT-based sensor network technologies facilitate the collection of real-time, actionable data to enhance decision-making, optimize resource use, and promote sustainable solutions in agriculture (5).

AI applications in agriculture span a wide range of areas, such as crop monitoring, pest and weed management, irrigation optimization, and yield prediction. For instance, AI-driven crop monitoring using machine vision and deep learning enables the early detection of nutrient deficiencies and diseases, allowing for timely interventions that reduce crop losses (2). Similarly, robotics and autonomous systems equipped with AI are increasingly used in agriculture to perform tasks like soil sampling, precision spraying, and harvesting, thereby reducing labour costs and enhancing efficiency (6,7). Moreover, AI-powered irrigation management systems optimize water use by analysing real-time data on soil moisture, weather conditions, and crop water needs, contributing to significant water savings and improved crop health (8).

The purpose of this study is to explore the current state of AI applications in precision agriculture, highlight recent advancements, and discuss the challenges and future directions for integrating AI technologies into sustainable farming practices. Recent studies have demonstrated the potential of AI to revolutionize traditional agricultural practices, supporting a shift towards more sustainable and resilient food production systems (9,10). This study aims to provide insights into how AI-based methods contribute to optimizing agricultural operations and ensuring environmental sustainability.

Materials and Methods

Literature search strategy

The Preferred Reporting Items for Systematic Reviews (PRISMA) technique was used for systematic review (11,12). The search was performed in the Scopus database https://www-scopus-com.elibrarytnau.remotexs.in/. Various combinations of keywords related to AI in agriculture were considered, and the outcome of interest was used as input to search for research papers. The search strings used and the corresponding number of publications retrieved from the Scopus database in this systematic research study are given in Table 1. Each row in the table represents a particular keyword used by the researchers, while the last row indicates the total number of publications retrieved. The search strings are constructed to capture various dimensions of the artificial intelligence technologies used for precision agriculture.

Criteria for inclusion and exclusion

For the initial screening of the articles, inclusion and exclusion criteria were implemented to select relevant publications from the articles obtained from the Scopus database (Fig. 1). Using the automation filters provided by the databases, non-English, review papers, book chapters, and restricted access were deleted from the records. Publications from the specified subject areas, such as Agricultural and Biological Sciences, Environmental Science, Biochemistry, Genetics, and Molecular Biology were included. Research articles written in English from open-access journals published between 2000 and 2024 were included using inclusion criteria.

Relevance, duplicate removal and quality evaluation

Further extraction of articles involved screening the titles and abstracts of the remaining articles. Studies were included based on the presence of predefined keywords related to artificial intelligence in agriculture in the title, abstract or keywords section of the paper and the studies that focus on precision agriculture and sustainability as a key outcome. Studies that failed to exhibit these characteristics or did not include the relevant keywords were

Table 1. Keywords and search strings used and the total number of publications from the Scopus database

S. No.	Search strings	Number of publications
1	“Artificial Intelligence” AND “Agriculture” AND “Precision Agriculture”	1089
2	“Artificial Intelligence” AND “Agriculture” AND “Machine learning”	2028
3	“Artificial Intelligence” AND “Agriculture” AND “IoT”	1226
4	“Artificial Intelligence” AND “Agriculture” AND “Agricultural Robots”	694
5	“Artificial Intelligence” AND “Agriculture” AND “GIS”	195
6	“Artificial Intelligence” AND “Agriculture” AND “Remote sensing”	534
7	“Artificial Intelligence” AND “Agriculture” AND “Automation”	646
8	“Artificial Intelligence” AND “Agriculture” AND “Crop management”	179
9	“Artificial Intelligence” AND “Agriculture” AND “Sustainability”	666
10	“Artificial Intelligence” AND “Agriculture” AND “Image analysis”	130
11	“Artificial Intelligence” AND “Agriculture” AND “Yield prediction”	166
12	“Artificial Intelligence” AND “Agriculture” AND “Crop yield”	541
13	“Artificial Intelligence” AND “Agriculture” AND “Crop quality”	51

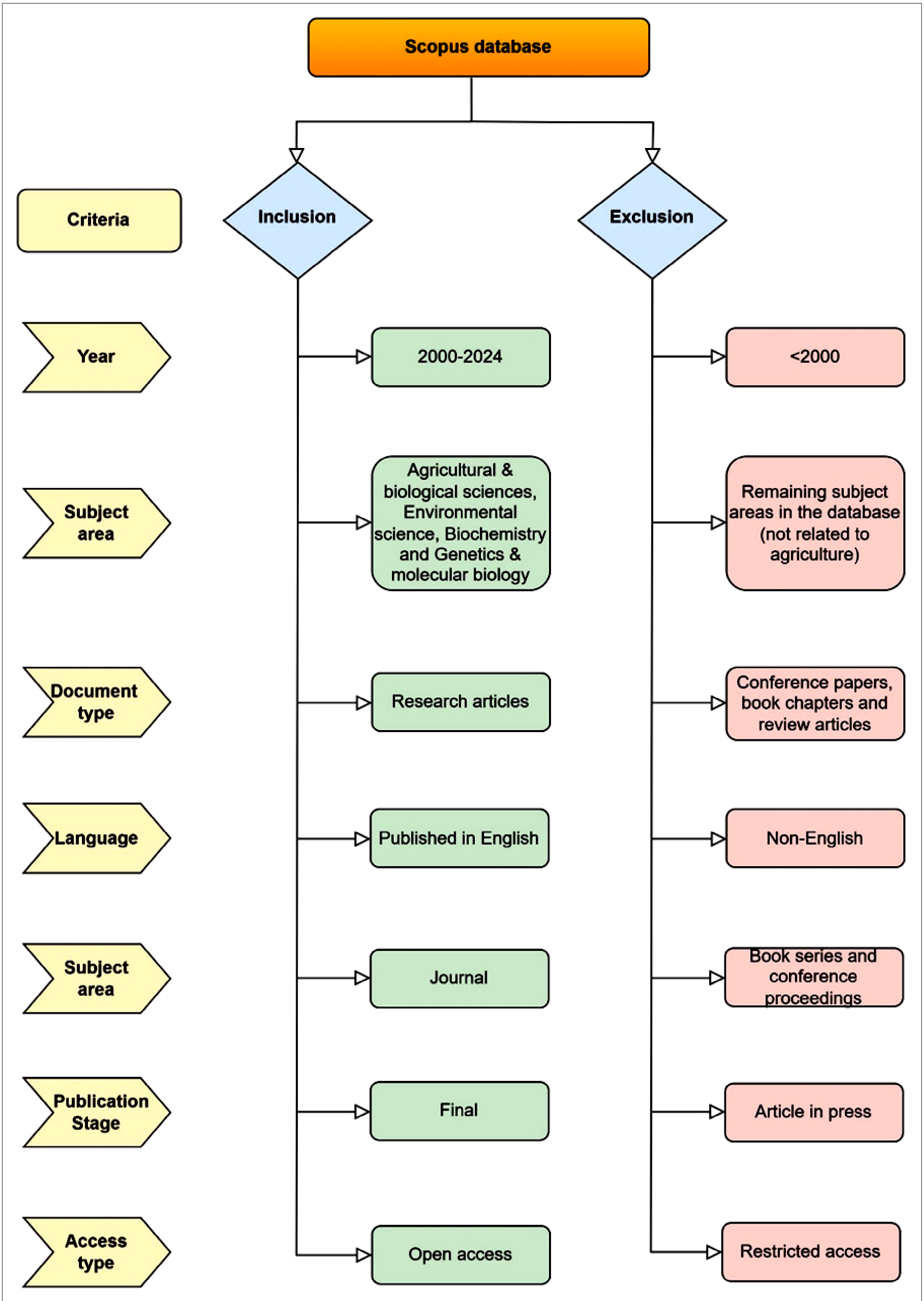

Fig. 1. Flowchart illustrating the inclusion and exclusion criteria for selecting articles from the Scopus database for analysis.

excluded. Based on the eligibility criteria of including, some studies were excluded from the available literature after a thorough screening of the full text which is not relevant to artificial intelligence in agriculture. Finally, the eligibility assessment phase included all original research articles aiming at precision agriculture for sustainability through artificial intelligence.

Bibliometric analysis

The bibliometric analysis of all the eligible articles was analysed using R-Studio and VOS viewer to identify annual scientific production, organization networks, and keywords networks. Thematic mapping, highlighting the need for a strategy for future research projects on artificial intelligence in precision agriculture, was created using R-Studio by uploading all 76 full articles.

Results

The PRISMA flow diagram was used to depict the number of studies that were finally taken for systematic literature review (Fig. 2). This systematic literature review provided an overview of the existing literature on artificial intelligence in agriculture. Initially, a Scopus database search using various combinations of search strings resulted in a total of 8145 articles from the most diverse disciplines. From the automation filters provided by the database, 7433 articles were marked as ineligible using the inclusion and exclusion criteria during the initial identification (e.g. non-English, restricted access, etc.) and deleted from the records.

The remaining 712 articles underwent further screening based on the title and abstract. After the

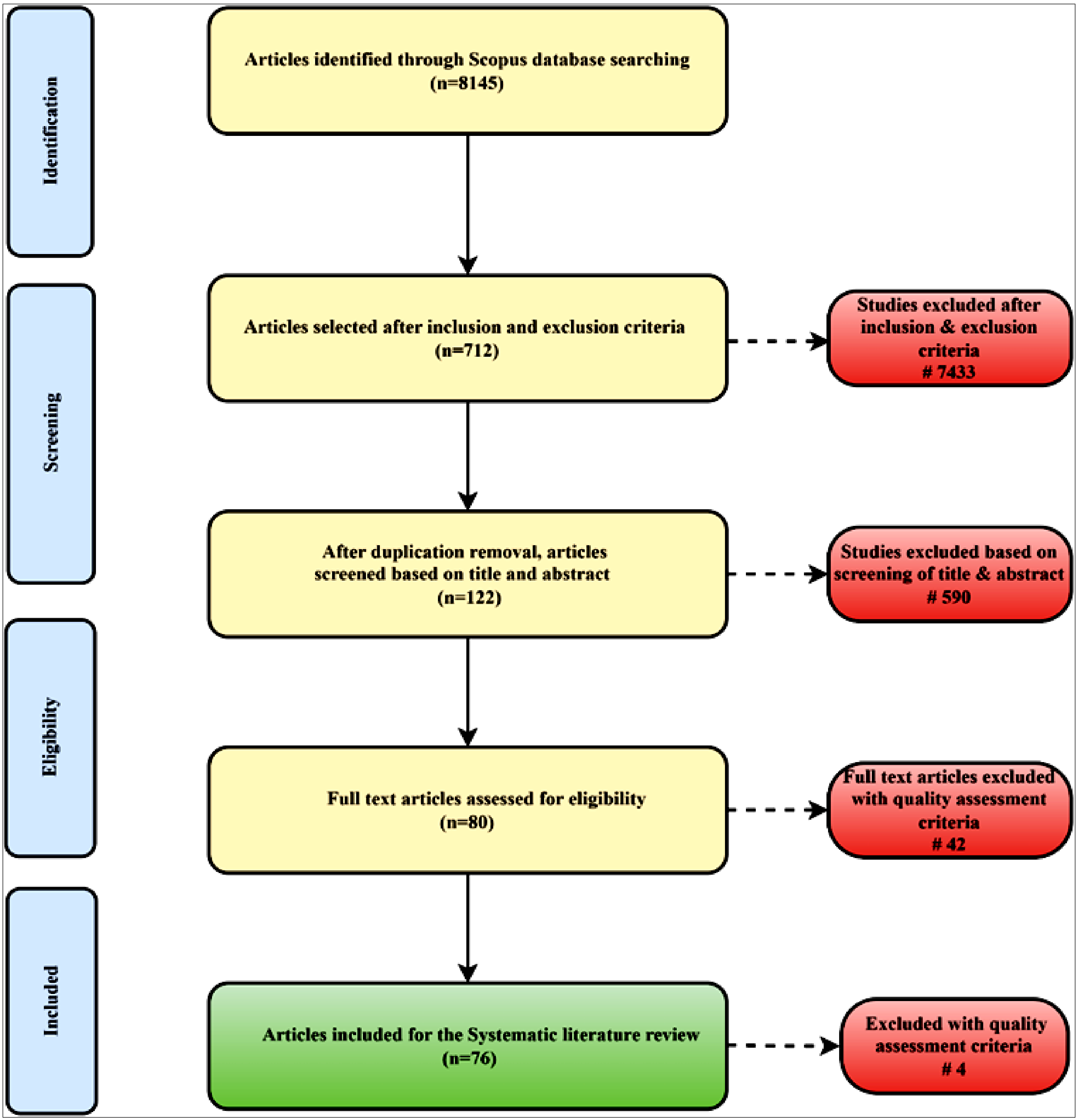

Fig. 2. The PRISMA flow diagram depicting the selection process and number of studies taken for systematic review.

screening, 590 articles were eliminated for the non-existence of predefined keywords in the title, abstract or keywords part of the paper. The remaining 122 articles underwent a thorough screening of the full-text articles and eliminated 42 research studies. Based on the eligibility criteria, the remaining 80 articles were subjected to a detailed quality assessment to ensure that only high-quality research was included in the systematic review. During this assessment phase, 42 articles were excluded for failing to meet the quality benchmarks set for the review. Consequently, 76 articles were selected for inclusion in the final systematic literature review, with an additional 4 articles excluded in the last stage due to non-compliance with quality assessment criteria. This selection process enabled a comprehensive analysis of relevant literature on the role of artificial intelligence in transforming precision agriculture for sustainability (2,3,6–10,13–81).

Optimizing crop health and water use: Crop monitoring and irrigation management

AI technologies are transforming agriculture in crop monitoring, where machine learning and computer vision are used to assess plant health and detect stress signals in real time (Table 2). Techniques such as UAV imaging and deep learning enable precise estimation of biomass and plant height which improve data-driven crop management decision-making (2,26,48). The intelligent irrigation system utilizes AI-powered technologies to optimize water usage

Table 2. Current applications of AI in precision agriculture, methods and key findings

Application area	Methods/techniques used	Key findings/results	References
		Crop monitoring	
Crop monitoring Nitrogen content	Hybrid DCNN-LSTM model, image analysis, deep learning	The hybrid model achieved high accuracy (R^2 = 0.904) in predicting nitrogen content in muskmelon.	(26)
Coffee crop monitoring	YOLOv7, computer vision, semi-supervised learning	Achieved 0.89 mAP for fruit detection, improving accuracy, yield estimation	(36)
Non-destructive crop growth monitoring	Convolutional Neural Network for estimating leaf area and fresh weight	Achieved R^2 values of 0.95 for leaf area estimation and 0.70 for fresh weight estimation	(29)
Crop stress detection	Multi-rotor small unmanned aerial systems (sUAS) with intra-canopy sensors for stress diagnosis	Achieved timely detection of stress factors, providing near real-time stress diagnosis using RGB imagery	(34)
UAV-based rootstock evaluation	UAVs with multispectral imaging and AI algorithms for phenotyping	Achieved 99.9% accuracy in tree detection and high correlation (R=0.84) in canopy size estimation compared to manual methods	(80)
Maize height estimation	UAV, satellite, ML (Random Forest), vegetation indices	High accuracy in estimating maize height, with a strong correlation to the manual method	(48)
Lettuce pigment phenotyping	Integration of reflectance spectroscopy with AI algorithms (AdaBoost, Neural Network)	Achieved high accuracy (>99%) for pigment content across multiple lettuce varieties using hyperspectral data	(19)
Real-time crop monitoring	AI-enhanced push-broom hyperspectral imaging for plant identification	Achieved 99.6% accuracy in classifying plant species at a high frame rate (50 fps)	(23)
Phosphorus content detection in plants	Hyperspectral imaging and machine learning (SVM, RF, BNN)	Achieved over 80% accuracy in identifying phosphorus levels across different plant species and growth stages	(30)
Plant stress detection	Low-cost thermal imaging with AI-based image segmentation models (SVM and SegNet)	Achieved an R^2 correlation of 0.75 with commercial thermal cameras for monitoring crop water stress	(72)
Rice growth prediction	Artificial Neural Network and Gene-Expression Programming combined with GDD modeling	ANN and GEP outperformed traditional methods, with GEP showing the lowest RMSE (3.83) for rice growth stage prediction	(53)
Greenhouse monitoring	Multilayer Perceptron for predicting plant growth based on LoRaWAN data	Achieved a root mean square error (RMSE) of 10% in predicting weekly plant growth	(24)
		Irrigation	
Precision irrigation in legume farming	AI, machine learning, remote sensing, real-time monitoring	AI-driven precision irrigation optimizes water use, boosts crop yields, and conserves resources by adjusting irrigation based on environmental and crop data	(50)
Automated irrigation	IoT, SDI-12 sensors, cloud monitoring	The system improves water use efficiency by enabling real-time soil moisture control and remote irrigation management.	(73)
Irrigation scheduling for Maize	Hybrid LSTM model, Aquacrop simulations, remote sensing	LSTM model accurately predicts soil moisture reductions, improving irrigation precision and water management	(32)
Intelligent irrigation for Rice	IoT, automatic control, cloud-based systems, remote telemetry	The system enhanced water-saving significantly, achieving a reduction in water use by 2.9–19.3% across various seasons.	(8)
Smart irrigation management	AI and Big Data analytics integrating XGBoost and ERA5-Land reanalysis data	Achieved R^2 = 0.97 for Evapotranspiration estimation, improved irrigation management	(38)
Predictive irrigation management	Multi-layer perceptron (MLP), support vector machine (SVM), k-nearest neighbours (KNN)	Achieved water savings of up to 27.6% and energy savings of up to 57% by optimizing irrigation schedules	(67)

Yield			
Yield estimation	Deep learning (YOLOv3, DeepSORT), geospatial mapping	Achieved 91–95% accuracy in apple counting, with optimized visualization and harvest	(25)
Carrot yield and quality prediction	Artificial Neural Network, Random Forest, Multiple Linear Regression using satellite vegetation indices	ANN showed superior performance with $R^2 = 0.68$, outperforming RF ($R^2 = 0.67$) and MLR ($R^2 = 0.61$) for yield prediction	(37)
Citrus yield prediction	UAV multispectral imaging combined with ground-based fruit detection using YOLOv3 and ML algorithms	Model-2 achieved a MAPE of 23.45%, offering the best accuracy among tested approaches for tree-level yield prediction	(49)
Predicting mass flow in Sugarcane harvesting	NARX neural networks for multi-sensor data fusion	Achieved 0.3 kg/s RMSE and 0.7% MAPE, outperforming traditional linear regression	(17)
Grape bunch detection	YOLOv4 object detection for identifying grape bunches	Achieved an R^2 of 0.83 in grape bunch detection with a low error rate of 1.12 bunches	(52)
Weeds			
Robotic weed removal	Mixed-autonomous robotic platform with RGB-D cameras and gantry robot	Achieved over 97% accuracy in weed identification and 85% effectiveness in weed removal with minimal crop damage	(68)
Robotic weeding in agriculture	Autonomous weeding robots, RTK-GPS, camera -guided systems	Robots achieved 87% weed control efficacy, with the potential to reduce herbicide use by up to 83% in sugar beet and rapeseed.	(15)
Weed detection using deep learning	CNNs, YOLO variants, U-Net, SegNet for image classification	Improved weed identification accuracy with deep learning models	(61)
Precision weed management	AI-based machine vision and deep learning for weed detection and selective spraying	Achieved 91% accuracy for detecting artificial weeds and 71% precision in real field conditions	(76)
Early weed identification	YOLOv5 and YOLOv8 CNNs for detecting weed species in wheat fields	Achieved an average precision (AP) greater than 0.6 for several weed species, enabling early weed management decisions	(69)
Pest and Diseases			
Cotton disease detection	CANnet architecture incorporating RFSC and PCA modules for feature extraction	Achieved 96.3% accuracy on self-built dataset and 98.6% on public dataset for cotton disease identification	(75)
Watermelon disease detection	Multilayer Perceptron (MLP) and Decision Tree (DT) classifiers for hyperspectral imaging analysis	MLP achieved 90% classification accuracy for high disease severity stages, showing better performance than DT for detecting downy mildew stages	(39)
Tomato leaf disease detection	Optimized MobileNetV2 model for classifying tomato leaf diseases	Achieved 98.3% accuracy and 94.9% recall in identifying six types of tomato leaf diseases	(51)
Pest damage detection	Decision Trees algorithm for identifying damage intensity from images	Achieved a precision of 0.98 and an accuracy of 0.99 in classifying pest damage on tomato leaves	(66)
Fungal contamination detection	Ghost-YOLOv4 for detecting sundry bacteria on Lentinula edodes logs	Achieved real-time detection with over 90% accuracy, enabling rapid identification and reduced contamination spread	(41)
Smart and Sustainable Agriculture			
Sustainable agriculture	AI, ML, big data, remote sensing, automation	AI enhances agricultural sustainability by optimizing resource use and improving decision-making, addressing economic, social, and environmental challenges	(45)
Sustainable precision farming	Integration of AI and IoT for resource management and decision support	Achieved 98.65% accuracy in precision farming applications with significant resource optimization benefits	(10)
AI for sustainable agriculture practices	Machine learning for precision water management and IoT for smart farming	Enhanced resource efficiency and reduced water wastage through AI-driven irrigation scheduling	(79)
Smart sprayers			
Site-specific UAS spraying	Feature Pyramid Network (FPN) and YOLOv5 for artichoke plant detection	YOLOv5 achieved better overall performance, with an F1 score of around 90% for detecting artichoke plants in real-time UAS spraying applications	(62)
Smart spraying system	LiDAR, machine vision, GPS, and sensor fusion for variable-rate tree spraying	Achieved a 28% reduction in spraying volume while maintaining effective coverage, reducing agrochemical waste	(28)

by predicting irrigation needs based on real-time weather data, which enhances water use efficiency in rice farming (8). The hybrid Long Short-Term Memory (LSTM) model developed for irrigation scheduling in maize integrated with crop simulation data further improves irrigation precision by accurately predicting soil moisture levels (32).

Precision control in the field: Weed and pest management and smart sprayers

AI-powered robotic systems are transforming weed and pest management by facilitating focused interventions. Computer vision enabled autonomous weeding systems reduce the need for herbicides, providing an effective, environment friendly method of weed management while maintaining high efficacy (6,14,15). Similarly, AI-based pest detection technologies can identify and monitor pest populations, facilitating timely and accurate pest management. Based on real-time field data analysis, smart sprayers integrated with AI technologies apply agrochemicals at variable rates. This approach reduces waste from chemical input, minimizes environmental impact, and optimizes agrochemical usage for crop protection (7). AI and IoT-based systems in precision farming facilitate targeted agrochemical applications, optimizing crop protection by reducing pesticide use and minimizing environmental impact (10). AI-powered data-driven approaches in agriculture enhanced the efficiency of agrochemical usage by providing precise, localized crop protection strategies based on environmental and crop-specific data (45). AI applications in sustainable agriculture aid in the optimization of agrochemical use by analysing crop health data to target specific pests and diseases, which reduces unnecessary chemical inputs and promotes eco-friendly practices (79).

Towards resilient farming: Sustainable agriculture and yield optimization

AI-driven technologies contribute to smart and sustainable agriculture by enhancing resource efficiency, reducing environmental footprints, and promoting resilience to climate change. AI applications in agriculture facilitate the transition to data-driven, eco-friendly farming practices (3,6,8). Yield optimization techniques, such as deep learning-based fruit counting (e.g., YOLOv3) and machine learning algorithms for biomass estimation, support accurate yield predictions and harvest planning, leading to better resource allocation (25,48).

Discussion

The Annual scientific production graph (Fig. 3) shows the number of research articles published each year related to artificial intelligence in precision agriculture. From 2008 to around 2020, fewer than 10 articles per year were published, which indicates the slow rate of publications. A noticeable increase in publications was observed from 2021 onward, exceeding 30 articles by 2023. This growth suggests an increasing interest and investment in this area of study, which is driven by advancements in AI and its uses in agriculture. The upward trend suggests that artificial intelligence in precision agriculture is gaining a major focus, reflecting its potential to increase agricultural efficiency and sustainability.

The keyword network (Fig. 4) depicts a network diagram of the most frequently used terminologies in AI-related precision agriculture studies. This network shows the interdisciplinary scope of the research, highlighting the interrelation of technological, agricultural, environmental, and economic aspects. Key terms such as "precision agriculture," "machine learning," "sensor," and "robotics" are closely interconnected, indicating the convergence of AI, data science, and agricultural practices. Additionally, connections with terms like "sustainability," "irrigation," and "crop production" indicate efficient and sustainable resource management and enhancing productivity. This interconnected network captures the collaborative efforts of diverse fields to address agricultural challenges through an integrated approach focused on sustainable precision farming.

A network diagram of collaborations among various research institutes and organizations engaged in AI applications for precision agriculture (Fig. 5). Institutes such as Leibniz Centre for Agricultural Landscape Research, Fraunhofer Institute for Intelligent Analysis and Information Systems and multiple computer science, geoscience, and agricultural engineering institutes emphasizes the multidisciplinary approach for advancements in this field. The collaborative nature of research in precision agriculture where expertise from agricultural sciences, computer

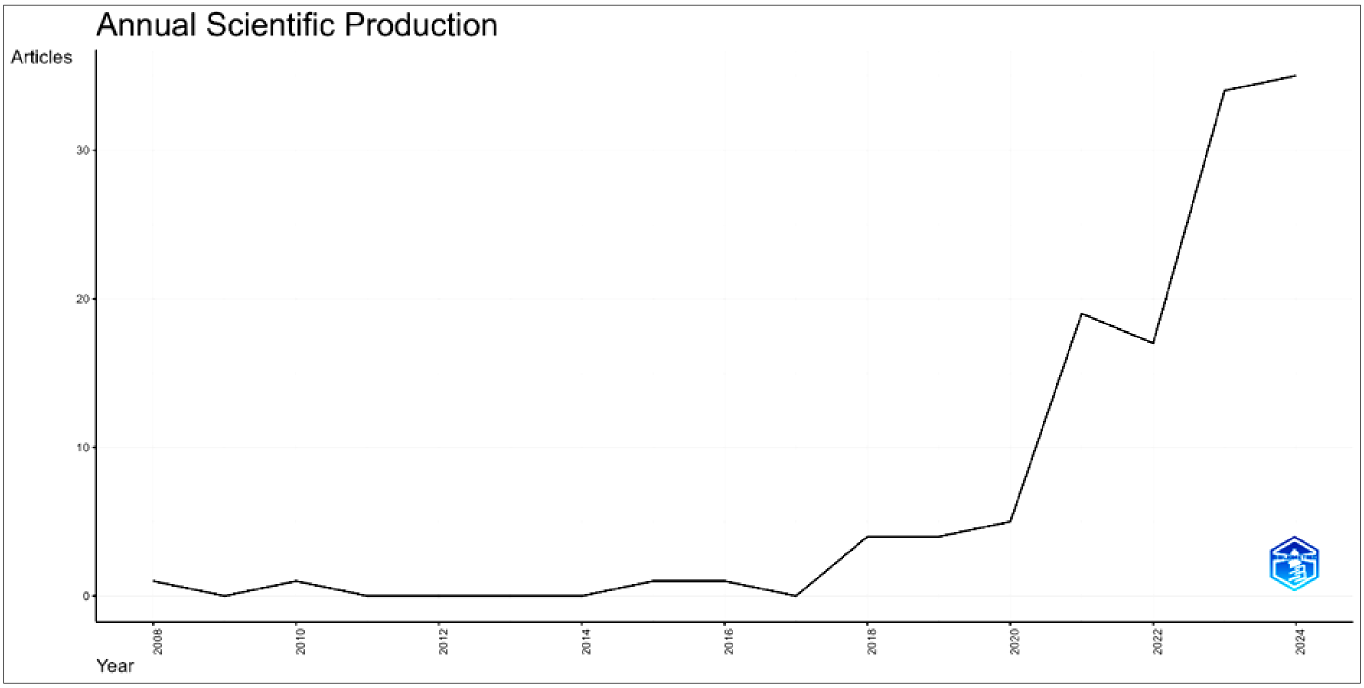

Fig. 3. Annual scientific production of research articles.

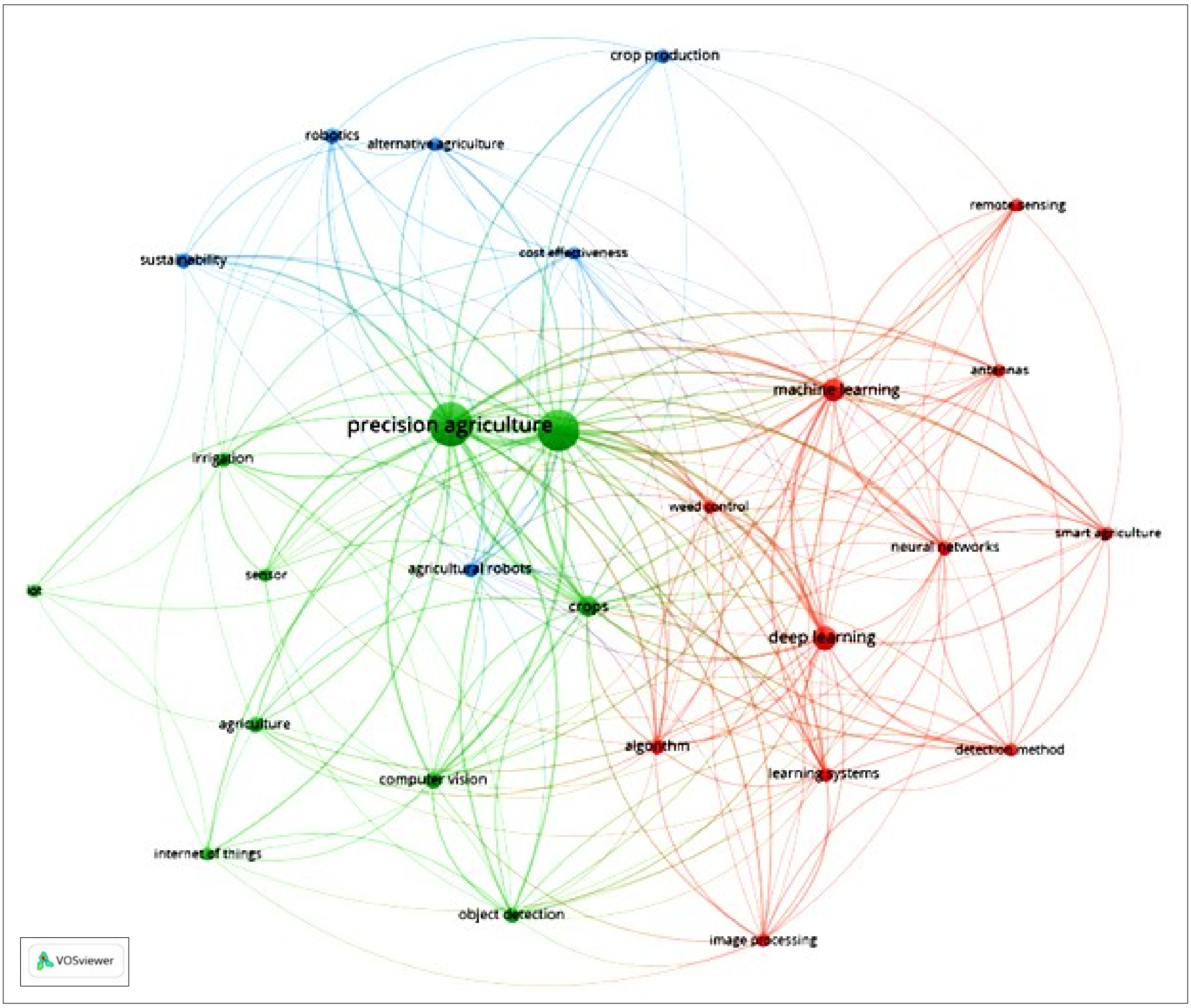

Fig. 4. Frequently used keywords network in research studies on artificial intelligence applications in precision agriculture.

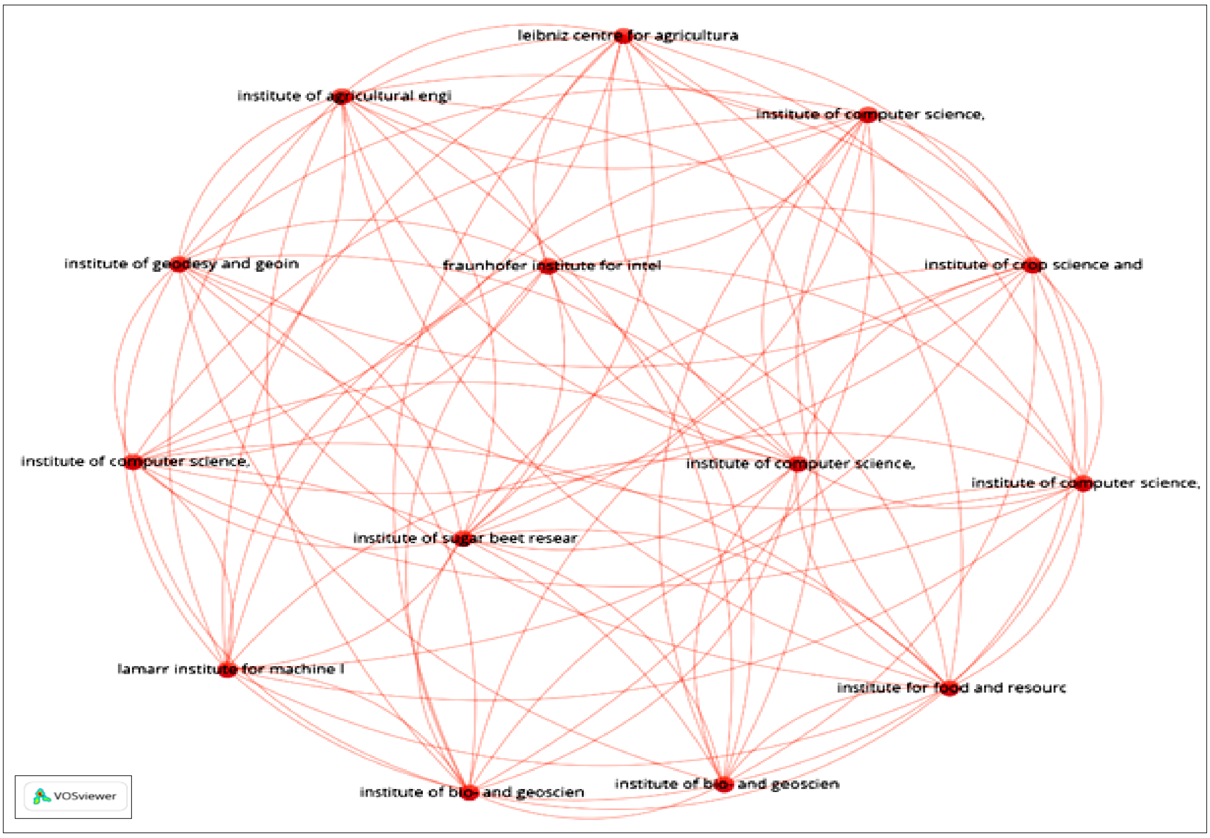

Fig. 5. Collaborative network among research institutes and organizations involved in artificial intelligence applications for precision agriculture.

science, geosciences and engineering converge to address complex sustainability challenges. This supports interdisciplinary innovation, advancing AI-based precision agriculture solutions that enhance efficient and sustainable farming practices.

Potential gap

The thematic map (Fig. 6) provides an overview of key research areas in AI-driven precision agriculture, dividing into four quadrants *i.e.*, Motor Themes, Niche Themes, Basic Themes, and Emerging or Declining Themes, based on centrality (relevance) and density (development stage). Motor themes, including "Smart Agriculture," "Artificial Intelligence," "Crop Production," "Sensor," "Robotics," and "Alternative Agriculture," are well-developed and highly relevant areas that form the foundation of AI applications. These themes indicate a research focus on the application of AI to enhance crop management and agricultural productivity. Niche themes with lower centrality are less integrated and remain less explored. The basic themes, which have not been classified in this map denote fundamental widely applicable areas; however, they remain less developed in terms of density from the selected articles. Emerging or declining themes include "Coffee," "Nitrates," and "Farming Systems," which exhibit both lower centrality and density indicating that they represent emerging topics and have potential for future research. This thematic map, therefore, underscores the significant role of core areas like "Precision Agriculture" and "Artificial Intelligence" while emerging themes hold promise for future research and development.

The thematic map identifies a notable research gap in the comprehensive integration of topics such as "Irrigation" and "Sensor" technologies within central AI applications in precision agriculture. Addressing this gap by linking specialized technologies with AI-driven frameworks could significantly improve resource efficiency, particularly in water and nutrient management, advancing sustainability objectives. This enhances resource efficiency and sustainability in agriculture by bridging these emerging and foundational themes.

Conclusion

The systematic literature review emphasizes the critical role of AI in addressing key agricultural challenges, including feeding a growing population, coping with climate change, and managing limited resources. AI provides advanced solutions for improving crop management, resource allocation, and sustainable farming methods to increase agricultural production by 50% by 2050. This study covers a diverse AI application that transforms agricultural practices such as crop monitoring, irrigation management, weed and pest control, yield prediction, and smart sprayers. AI-enhanced irrigation systems optimize water use based on sensor data and weather forecasts. These innovations improve water use efficiency and precision in irrigation scheduling. AI-powered robotic systems targeted weed and pest management, reducing chemical inputs and promoting sustainable agriculture. In yield estimation, AI models facilitate accurate predictions which helps in better harvest planning and resource management.

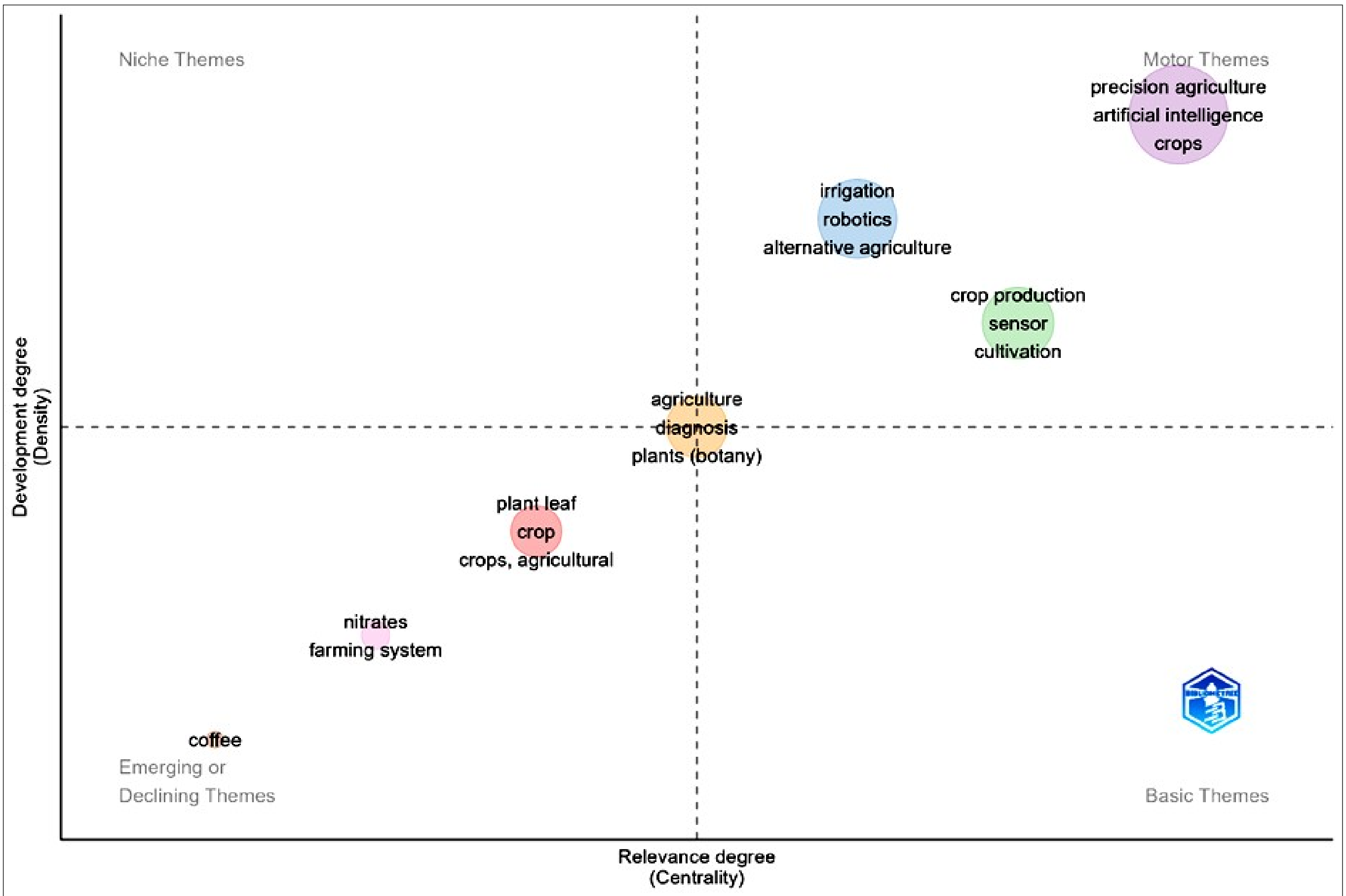

Fig. 6. Thematic analysis of research papers.

This study also identifies existing research gaps, particularly in integrating AI with emerging areas like nutrient management and the comprehensive use of sensor technologies for resource efficiency. Addressing these gaps could extend AI's impact on effective agricultural practices. AI-driven approaches with less explored themes, such as nitrate management and alternative farming systems, offer opportunities for future research. By addressing these gaps, AI has the potential to drive the transformation of agriculture towards resilience and sustainability.

Acknowledgements

We sincerely acknowledge Tamil Nadu Agricultural University for granting access to their extensive institutional database, which enabled to explore and consult high-impact journals indexed in Scopus. This access proved invaluable in sourcing comprehensive and credible research materials that significantly enriched the depth and quality of this review. Such resources have been instrumental in providing a strong foundation for the analysis and findings presented in this manuscript.

Authors' contributions

SPM and JD conceptualised the work, carried out the systematic literature review and drafted the manuscript. NS, JD, and VR carried out the graphical presentation. NS and MP edited the manuscript. PK and VR attended the editing work and coordination. SK and GS participated in editing the manuscript and sample analysis. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Rytr (blog/content writing AI software) to reframe certain sentences to incorporate appropriate research terminology in specific sections. Following the use of this tool, the authors carefully reviewed and revised the content as required, taking full responsibility for the accuracy and integrity of the publication content.

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