Artificial intelligence applications in agriculture: a systematic review of literature

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ABSTRACT

Artificial intelligence (AI) is transforming agriculture by offering innovative solutions to persistent challenges. This systematic literature review explores the most studied AI applications in agriculture, emphasizing crop management, agronomic decision-making, early detection of diseases and pests, and climate change adaptation. Using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology, 700 publications were retrieved from databases such as Scopus, ScienceDirect, and IEEE Xplore, with 104 relevant articles selected after applying strict inclusion and exclusion criteria. The findings underscore the importance of machine learning and image processing in tailoring agronomic practices to specific plot conditions and microclimates. These tools enable early identification and control of plant diseases and pests, reducing crop losses and dependence on chemicals. Nonetheless, challenges remain, particularly regarding accessibility for smallholder farmers, high implementation costs, and limited data infrastructure. While AI offers significant potential to enhance agricultural productivity, sustainability, and resilience, addressing these limitations is crucial. A balanced, inclusive approach is essential to ensure AI's benefits are widely distributed and contribute to long-term food security and environmental sustainability.

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1. INTRODUCTION

Agriculture has evolved through technological advances, new farming practices, and tools to improve food production and resource management [1]–[3]. It began as subsistence agriculture [4], where communities relied on hunting, gathering, and early domestication of plants and animals [5]. The development of farming techniques and primitive tools boosted food production and storage, enabling permanent settlements and the rise of early agricultural civilizations [6], [7]. This process led to today's precision agriculture era [8].

The agricultural revolution around 10,000 B.C. marked a pivotal shift with the introduction of advanced cultivation and domestication techniques, such as crop rotation and selective breeding [9], [10], significantly boosting food production and enabling population growth. Over the centuries, agricultural innovation persisted [11], with milestones like crop rotation in the middle ages and the 18th-century revolution marked by technologies such as iron plowing [12], [13] and sowing selected seeds [14]. In the 20th century, the green revolution introduced high-yielding crop varieties and widespread use of fertilizers and pesticides [13], which greatly increased production but also raised concerns about environmental impact and sustainability [13]–[16]. Looking ahead, agriculture must address rising demands. The Food and Agriculture Organization (FAO) projects the global population will exceed 9 billion by 2050, requiring a 60–70% increase in agricultural output [17]. In this context, innovation becomes critical. According to the World Bank, agricultural innovation and technology are essential for poverty reduction in developing regions [18], where nearly 80% of the extreme poor live in rural areas and rely on agriculture for their livelihoods. Therefore, sustainable technological advances in agriculture are not only vital for food security but also for socioeconomic development and environmental preservation. Today, we are in the midst of a transition towards precision agriculture and the application of information and communication technologies (ICT) in farm management [19], [20]. Technologies like sensors, drones, geographic information systems (GIS), and data analysis optimize resources and efficiency [21], [22]. Artificial intelligence (AI) and machine learning are increasingly applied in decision making [23] and in the early detection of diseases and pests [24], [25].

The use of AI in agriculture has grown significantly in recent years [26], [27], transforming crop management, decision-making, and production challenges. The integration of information technology, data analytics, and machine learning has enabled diverse AI applications [28]–[30] aimed at improving efficiency, productivity, and sustainability [31]. These applications include early detection of crop diseases [32], [33] monitoring of climatic conditions, and optimization of irrigation and fertilizer use [34]. AI also supports automation through robots and drones [35]–[37] and enhances decision-making with real-time data analysis [38].

This systematic review analyzes the most researched AI applications in agriculture, focusing on efficiency, decision making, sustainability, production quality, and ethical-economic challenges. It also explores how AI is transforming modern agricultural practices. The article is structured in five sections: i) introduction presents AI's transformative role, ii) methodology explains the selection of 104 studies using preferred reporting items for systematic reviews and meta-analyses (PRISMA), iii) results highlight applications such as irrigation and pest detection, iv) discussion examines benefits and implementation barriers, and v) conclusion underscores the need for equitable, sustainable AI adoption in the agricultural sector.

2. METHODOLOGY

This paper follows a structured approach to collect and analyze information. First, the PRISMA methodology was applied [39] to identify the most relevant articles. Second, bibliometric analysis was used [40] to detect common terms influencing the study of AI-based digital applications in agriculture. Lastly, key statistical factors and methods were reviewed in relation to bibliometric findings. According to PRISMA, the systematic review is structured into: i) type of study, ii) research questions, iii) search strategy, and iv) inclusion and exclusion criteria.

2.1. Type of study

A systematic review of the literature was used to prepare this article [41]. This process allows for the collection of relevant evidence on a given topic that. In addition to meeting the established eligibility criteria, provides answers to the research questions posed [42].

2.2. Research questions

Five questions were developed to cover the objectives and to identify relevant characteristics to answer the following research questions:

RQ1. What are the most researched AI applications in the agricultural sector based on published studies?

RQ2. What is the role of AI in the early detection and control of plant diseases and crop pests?

RQ3. How has AI influenced the customization of agricultural practices and adaptation to different climatic and soil conditions?

RQ4. How has AI influenced agricultural decision making, such as crop management, irrigation scheduling and fertilizer application?

2.3. Search strategy

This systematic review employed various strategies, terms, and resources to identify relevant studies on AI applications in agriculture [43]. Table 1 presents the search equations and terms used. In order to answer the research questions posed, articles were collected from the main databases such as: Scopus, IEEE Xplore, ScienceDirect, IOPscience, EBSCOhost, Taylor & Francis. A total of 700 articles were collected, using inclusion and exclusion criteria, which allowed the identification of 104 relevant articles, as shown in Figure 1.

Table 1. Search equations

Database	Equations
Scopus	"artificial intelligence" AND "AI" AND "agriculture" AND "cultivation"; "artificial intelligence" AND "AI" AND "agriculture"
ScienceDirect, IEEE Xplore, IOPscience	"artificial intelligence" AND ("smart farming" OR "intelligent agriculture" OR "intelligent farming")
EBSCOhost, Taylor & Francis	("artificial intelligence" OR "AI") AND ("smart farming" OR "intelligent agriculture" OR "intelligent farming")

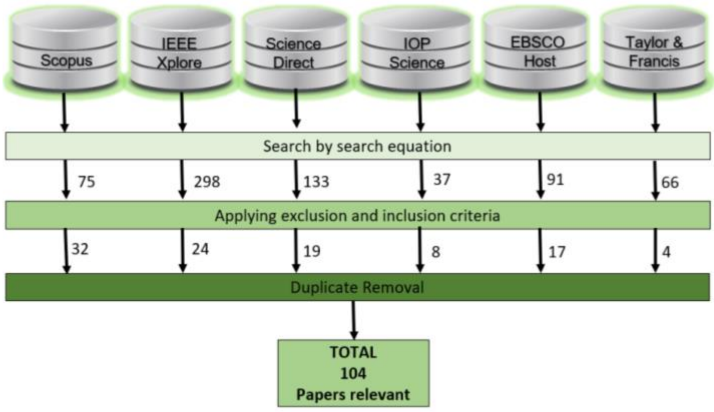


Figure 1. Selection methodology diagram

2.4. Inclusion and exclusion criteria

For the systematic review study, the following inclusion and exclusion criteria were applied, as shown in Table 2. These were established to ensure that the selected studies were relevant and up to date. Their application helped maintain the quality and consistency of the review.

Table 2. Inclusion and exclusion criteria

Inclusion	Exclusion
Studies investigating the most researched applications of AI in agriculture.	Studies that focus solely on the description of AI technologies without analyzing their application in agriculture.
Studies published in the last 8 years to ensure that the information is up to date.	Studies that focus only on the description of AI technologies without analyzing their application in agriculture.
Studies in languages relevant to your research.	Studies that do not provide sufficient detailed information on their methods and results.
Studies addressing different areas of AI application in agriculture, such as crop management, disease detection, and resource optimization	Duplicate studies found in multiple databases.

3. RESULTS

We analyzed 700 articles found in the database related to the research topic, of which 7 duplicate articles were rejected or did not contribute to the same research topic. After reviewing the articles, 693 articles were selected, 589 articles were excluded according to the exclusion criteria and did not contribute to answer the research question. We obtained 104 articles for systematic review as shown in Figure 2.

Bibliographic analysis allows the extraction of documents by identifying co-occurring words to detect patterns related to authors' work [40]. Bibliometrics measures scientific activity publications, citations, and collaborations and helps identify trends in a research field [44]. VOSviewer [45] is a tool used to analyze and visualize co-authorship, citation, and keyword networks [46] enabling graphical representations of scientific relationships. Based on this, visualization maps were generated as shown in Figure 3.

Figure 4 presents a word cloud generated from the analysis of the articles systematized in this review, offering a perspective on the most frequent themes and concepts in the field of study. Among the most prominent words are "agriculture," "machine learning," "deep learning," and "prediction". Figure 5 shows a tree map from a bibliometric analysis illustrating the most recurrent keywords in AI and agriculture research. The most frequent terms are "artificial intelligence" (8%), "deep learning" (5%), and both "agriculture" and "machine learning" (4% each). This visualization highlights the predominant themes and reflects current research focus areas in the application of AI to agriculture.

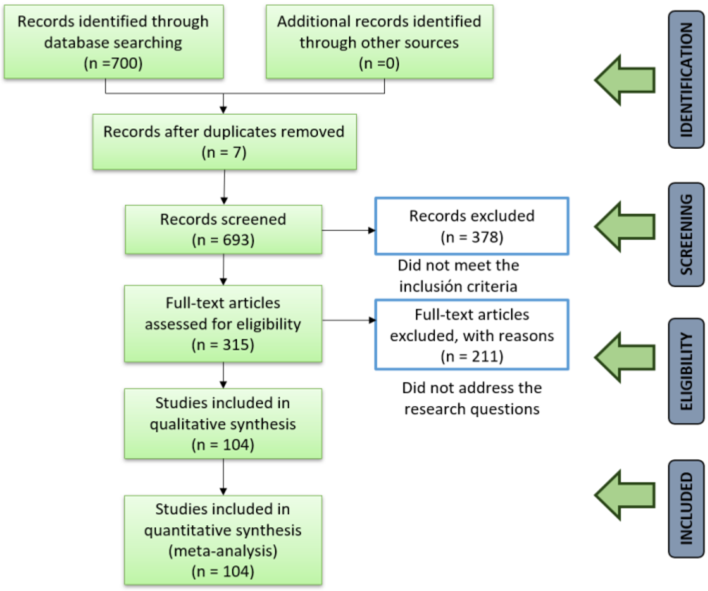


Figure 2. PRISMA diagram methodology

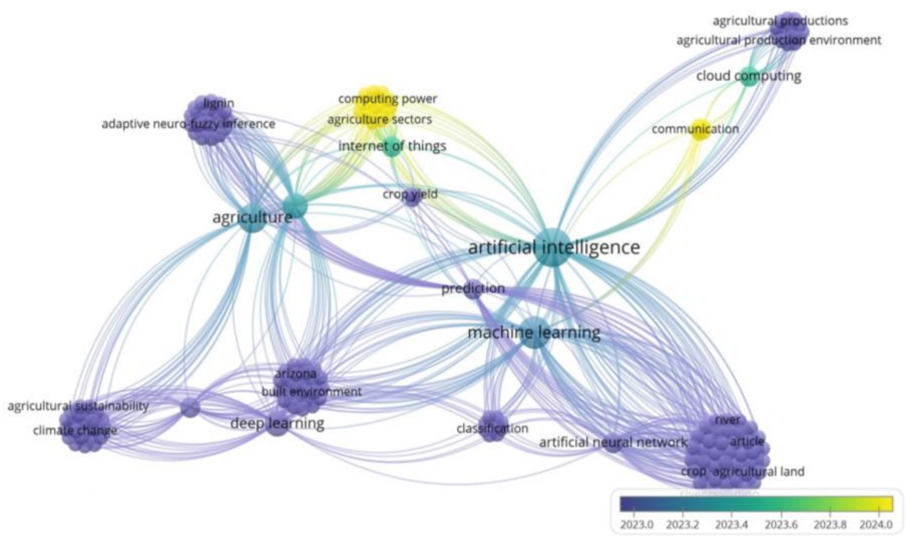


Figure 3. Network visualization of Scopus documents based on 163 bibliometric analyses

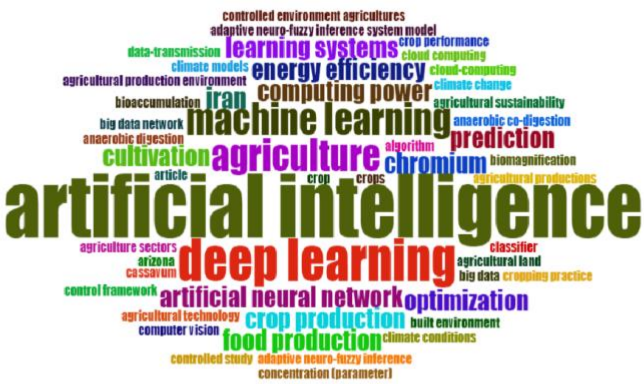


Figure 4. Word cloud

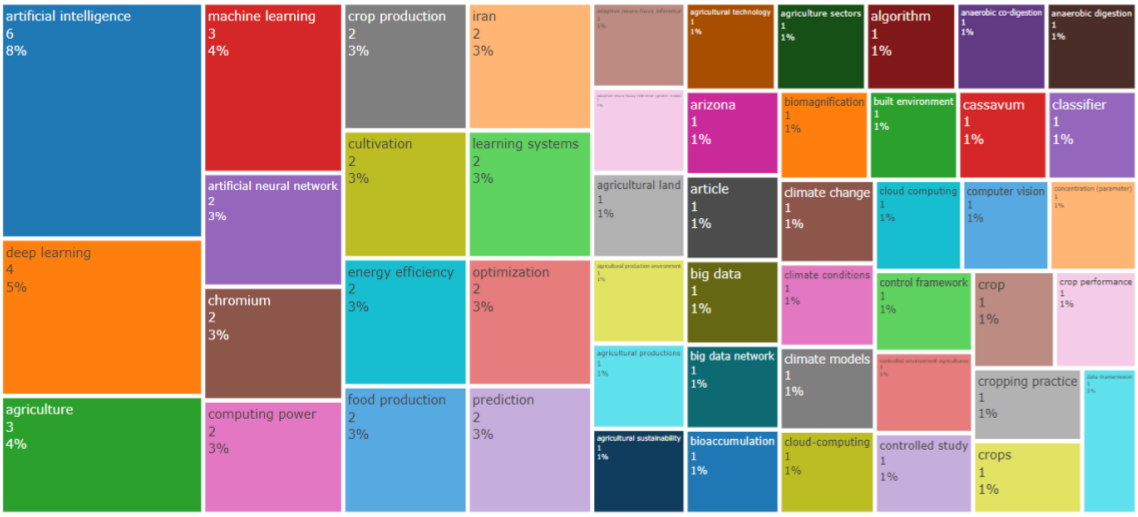
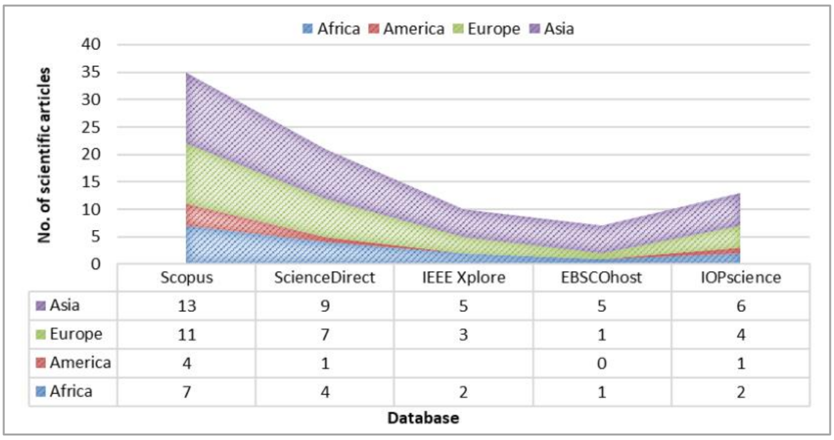


Figure 5. Tree map

Figure 6 presents the classification of the 104 articles analyzed, categorized according to the continent and the database in which they were published. The graph reveals that the largest amount of research on the application of AI in agriculture comes from the Asian continent. In addition, it is observed that these investigations are mainly concentrated in the Scopus database. The Figure 7 illustrates the number of articles published per year, broken down according to the source database: Scopus, IEEE Xplore, EBSCOhost, IOPscience, and ScienceDirect. In particular, it is noted that, in the year 2022, ScienceDirect registered a significantly high number of articles in relation to the search criteria used.



	Scopus	ScienceDirect	IEEE Xplore	EBSCOhost	IOPscience
Asia	13	9	5	5	6
Europe	11	7	3	1	4
America	4	1		0	1
Africa	7	4	2	1	2

Figure 6. Articles by database and continent

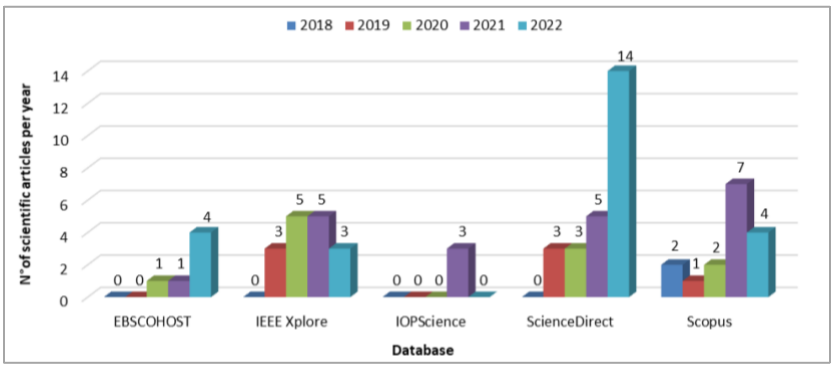


Figure 7. Articles by year and database

4. DISCUSSION

In this systematic review of the scientific literature, we analyze the most researched AI applications in agriculture, identify the most used models and algorithms, as well as their influence in different fields of agriculture, in order to answer the proposed questions.

4.1. Answer to research questions

4.1.1. RQ1: what are the most researched AI applications in the agricultural sector based on published studies?

Figure 8 shows the articles related to this topic, highlighting the most researched AI applications: "Disease and pest detection" with 32 articles, "Irrigation optimization" with 19 articles, and "Crop selection and breeding" with 17 articles. These areas represent the main focus of AI research in agriculture. They reflect the growing interest in improving crop health, resource management and genetic advances through AI technologies.

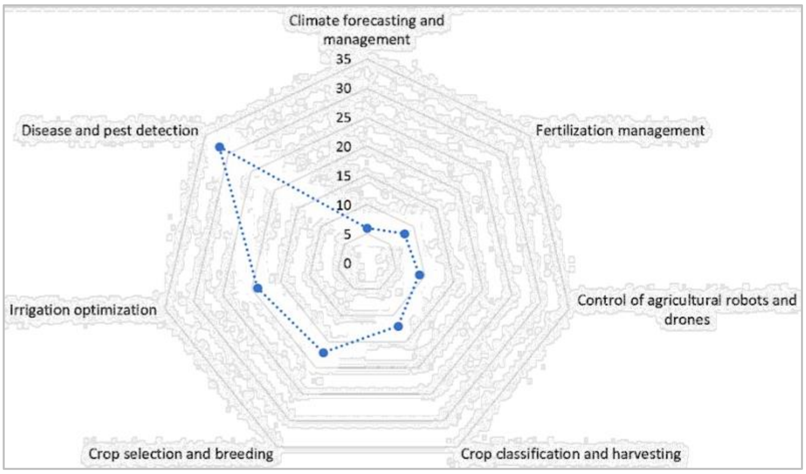


Figure 8. Articles by AI applications

From Table 3 it can be seen that AI-based applications are transforming various aspects of agriculture, from the detection of plant health problems, with the use of machine learning algorithms to identify and predict plant diseases and pests. These applications enable a faster and more accurate response to production optimization and resource management. AI applications are becoming more intelligent over time, thanks to machine learning, which allows them to further improve production operations.

Table 3. AI Applications used in the agricultural sector

Application of AI in agriculture	Description	Articles
Disease and pest detection	Use of machine learning algorithms to identify and predict plant diseases and pests, enabling a faster and more accurate response	[47]–[78]
Irrigation optimization	Use of sensors and algorithms to determine the optimal timing and amount of irrigation, based on real-time data of soil and weather conditions	[79]–[97]
Fertilization management	AI application to recommend the amount and type of fertilizers to be used, considering soil composition and specific crop needs	[98]–[105]
Crop classification and harvesting	Implementation of computer vision algorithms for sorting and selecting ripe crops for harvesting, reducing waste and optimizing yields	[106]–[117]
Climate forecasting and management	Use of historical and real-time climate data together with AI models to predict weather patterns, enabling informed decision making in agricultural management.	[118]–[123]
Control of agricultural robots and drones	AI used to guide and control robots and drones in agricultural tasks such as planting, crop monitoring, and pesticide application	[124]–[132]
Crop selection and breeding	Application of machine learning techniques to analyze genetic and phenotypic data and predict desirable crop traits, accelerating the breeding process.	[133]–[149]

Figure 9 shows studies that apply the above techniques and algorithms in specific agricultural contexts. These examples illustrate how different AI approaches have been used to address various challenges in agriculture. Table 4 groups the main applications of AI in agriculture according to the AI technique used as applied to agriculture. This table provides key examples of how different AI techniques and algorithms have been applied in agriculture. Among the techniques can be identified: supervised machine learning, deep learning, sensor networks, machine learning, fuzzy logic, unsupervised machine learning, and artificial neural networks.

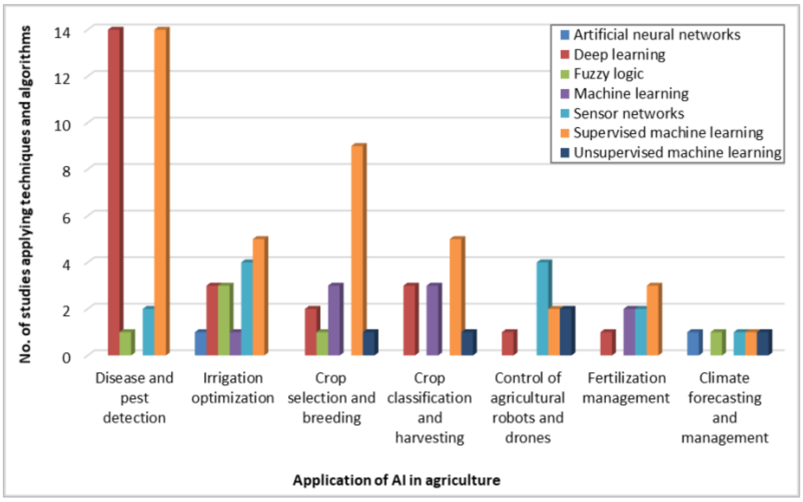


Figure 9. Applications by AI model and technique

Table 4. AI applications used in the agricultural sector

Application of AI in agriculture	AI technique	Articles
Disease and pest detection	Supervised machine learning	[49], [51], [53], [54], [56]–[59], [70]–[72], [74]–[76]
	Deep learning	[47], [52], [55], [60]–[69], [77]
	Sensor networks	[73], [78]
	Fuzzy logic	[48]
Irrigation optimization	Supervised machine learning	[85], [88], [91], [93], [94]
	Sensor networks	[84], [89], [92], [97]
	Deep learning	[79], [80], [82]
	Fuzzy logic	[83], [86], [87]
	Machine learning	[81]
	Artificial neural networks	[90]
Crop selection and breeding	Supervised machine learning	[134], [136], [137], [139]–[141], [143], [144], [148]
	Machine learning	[133], [135], [147]
	Deep learning	[142], [146]
	Unsupervised machine learning	[145]
	Fuzzy logic	[138]
Crop classification and harvesting	Supervised machine learning	[107], [110], [111], [115], [116]
	Deep learning	[108], [109], [112]
	Machine learning	[106], [113], [114]
	Unsupervised machine learning	[117]
Control of agricultural robots and drones	Sensor networks	[124], [125], [127], [128]
	Unsupervised machine learning	[130], [131]
	Supervised machine learning	[126], [129]
	Deep learning	[132]
Fertilization management	Supervised machine learning	[99], [102], [105]
	Sensor networks	[103], [104]
	Machine learning	[100], [101]
	Deep learning	[98]
Climate forecasting and management	Supervised machine learning	[118]
	Artificial neural networks	[121]
	Unsupervised machine learning	[120]
	Fuzzy logic	[123]
	Sensor networks	[119]

Figure 10 analyzes the types of AI techniques used in agriculture. "Supervised machine learning" leads with 39 articles, enabling plant disease detection, crop classification, and weed identification through image analysis [150]. "Deep learning" follows with 24 articles, using recurrent neural networks (RNN) and generative adversarial networks (GAN) to forecast crop yields from climatic data and generate synthetic images for training disease detection models. Table 5 and Figure 11 show the models or algorithms used in AI applications in the agricultural sector. Among the most prominent are: convolutional neural networks (CNN), support vector machines (SVM), linear regression (LR), and random forest (RF).

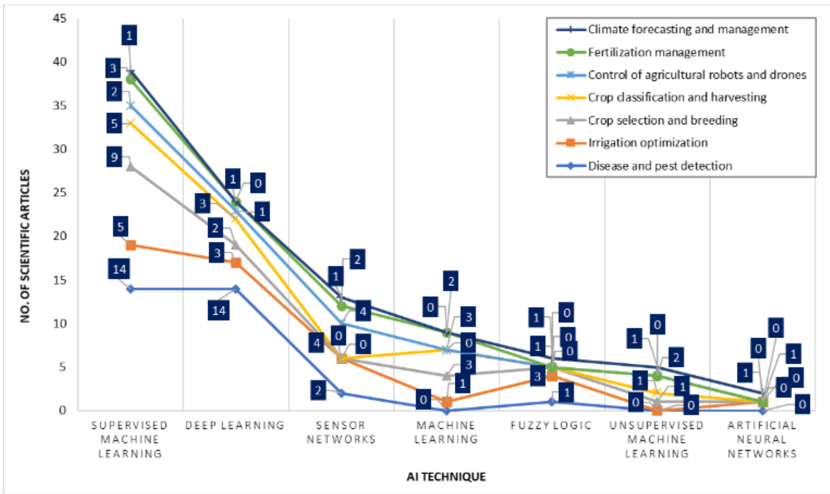


Figure 10. Articles on AI techniques and their application in agriculture

Table 5. AI model algorithm used in the agricultural sector

Model-algorithm	Application of AI in agriculture	Articles
CNN	Disease and pest detection	[47], [49], [54], [55], [59]–[64], [66], [67], [69], [71], [77]
	Crop classification and harvesting	[108]–[112], [116]
	Crop selection and breeding	[133], [140], [143]
	Fertilization management	[99], [102]
	Control of agricultural robots and drones	[129]
SVM	Crop selection and breeding	[146], [148]
	Irrigation optimization	[85], [94]
	Disease and pest detection	[58]
LR	Crop classification and harvesting	[113]
	Disease and pest detection	[75]
	Fertilization management	[100]
	Irrigation optimization	[88]
	Crop selection and breeding	[147]
RF	Crop selection and breeding	[136], [141]
	Climate forecasting and management	[118]
	Irrigation optimization	[91]

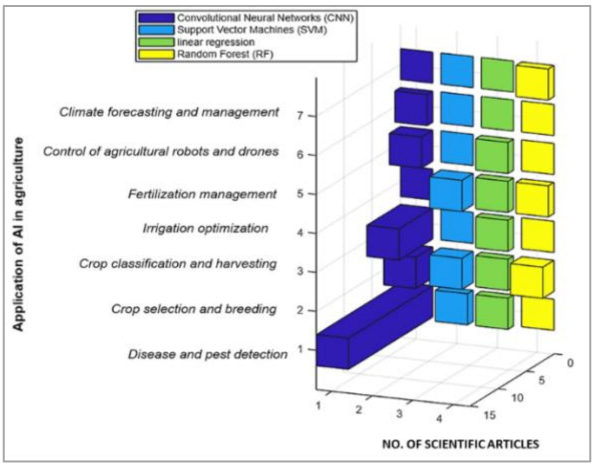


Figure 11. Articles by application and AI algorithm

4.1.2. RQ2. What is the role of AI in the early detection and control of plant diseases and crop pests?

Figure 12 shows the articles analyzed for the role of AI in the early detection and control of plant and crop diseases. Such studies that apply AI in the early detection and control of plant diseases and crop pests. These examples illustrate how AI has revolutionized the ability of farmers to identify and manage plant health problems more efficiently.

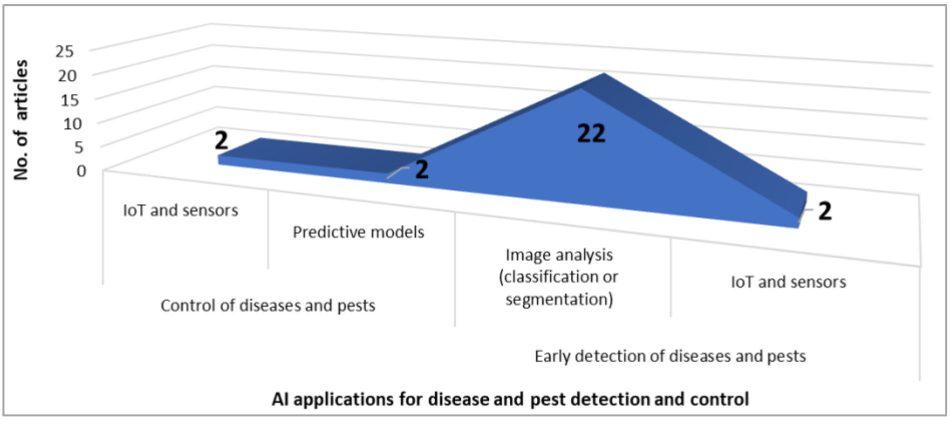


Figure 12. Articles by relevance in the detection of diseases and pests

Table 6 analyzes the most researched AI applications for detecting and controlling diseases and pests in agriculture. For early detection, image analysis of leaves and crops helps identify disease patterns, while sensors monitor environmental changes indicating plant health issues. For control, AI enables precise treatment application, predictive models to forecast outbreaks, sensor-based alerts, and algorithms to anticipate disease and pest spread and implement preventive actions.

Table 6. Articles analyzed according to AI applications in the detection and control of diseases and pests

Role of AI in detection and control	AI applications	Articles
Control of diseases and pests	IoT and sensors	[50], [78]
	Predictive models	[68], [112]
Early detection of diseases and pests	Image analysis (classification or segmentation)	[47]–[49], [51], [53]–[63], [65]–[67], [69], [70], [72], [77]
	IoT and sensors	[73], [74]

4.1.3. RQ3. How has AI influenced the customization of farming practices and adaptation to different climatic and soil conditions?

AI offers great opportunities to improve farming practices, the present graph of Figure 13 shows studies that apply AI in customizing farming practices and adapting to changing conditions. These studies illustrate how AI has enabled farmers to adapt their strategies to specific environments and circumstances to optimize production and sustainability. Table 7 groups how AI has influenced the customization of agricultural practices and adaptation to different climatic and soil conditions.

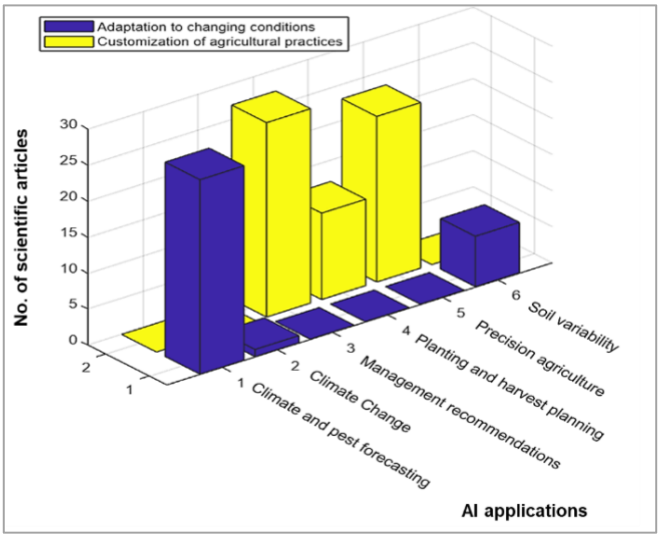


Figure 13. Articles on the influence of AI on the customization of agricultural practices and adaptation to climatic conditions

Table 7. Articles by influence on the customization of agricultural practices and adaptation to different climatic and soil conditions

AI influence category	AI applications	Articles
Adaptation to changing conditions	Climate and pest forecasting	[47]–[52], [54]–[60], [62]–[65], [67]–[70], [72], [74], [75], [77], [78], [111]
	Climate change	[121]
	Soil variability	[81], [84], [94], [98], [118]–[120]
Customization of agricultural practices	Management recommendations	[61], [82], [83], [85], [88], [99], [100], [101], [104], [107], [110], [113], [116], [117], [122], [125], [127], [130], [133], [135]–[137], [139], [141], [146], [148], [151]
	Planting and harvest planning	[53], [79], [87], [89]–[91], [93], [96], [97], [114], [132], [138]
	Precision agricultura	[66], [73], [80], [86], [92], [95], [102], [103], [106], [108], [109], [112], [115], [124], [126], [128], [129], [131], [134], [140], [142], [147], [149]

4.1.4. RQ4. How has AI influenced agricultural decision making, such as crop management, irrigation scheduling and fertilizer application?

Figure 14 shows studies that address AI applications in crop management, irrigation scheduling and fertilizer application. These articles illustrate how AI has influenced agricultural decision making to improve efficiency and sustainability. Table 8 summarizes AI's impact on agricultural decision-making, especially in crop management. It highlights yield prediction using climate and soil data with machine learning, irrigation optimization through sensor analysis, and real-time fertilizer adjustments based on soil nutrients. AI also recommends fertilizer types and amounts by analyzing soil and crop characteristics, enhancing precision and efficiency in managing essential aspects of crop production.

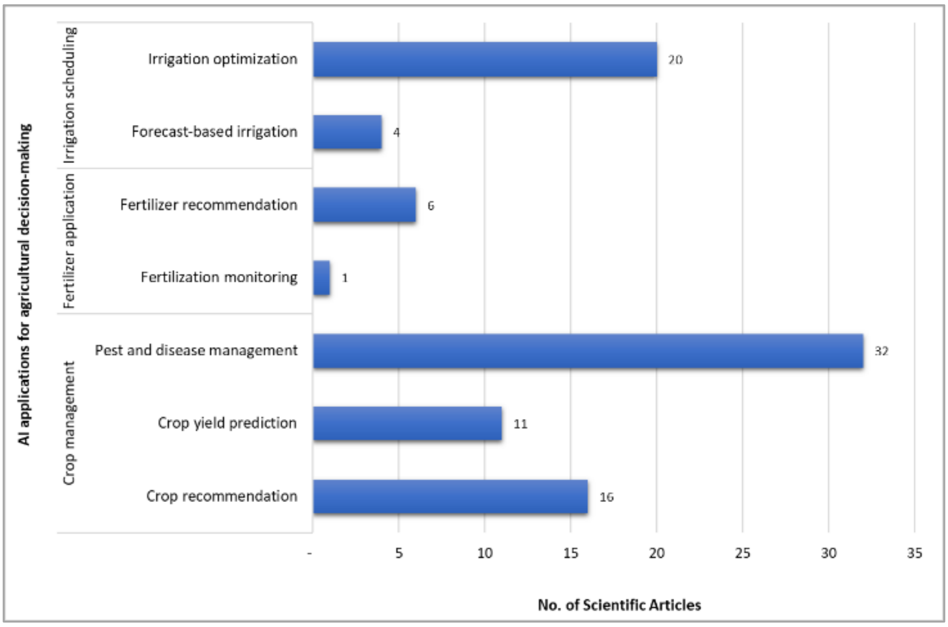


Figure 14. Articles on the influence of AI in agricultural decision making

Table 8. Articles grouped by the influence of artificial AI in agricultural decision making

Decision-making category	AI applications	Articles
Crop management	Crop recommendation	[88], [108]–[110], [114], [116], [119], [131], [133], [139]–[142], [147]–[149]
	Crop yield prediction	[94], [95], [106], [113], [115], [117], [134]–[136], [138], [146]
	Pest and disease management	[47]–[51], [53]–[70], [72]–[75], [77], [78], [111], [112]
Fertilizer application	Fertilization monitoring	[98]
	Fertilizer recommendation	[99]–[104]
Irrigation scheduling	Forecast-based irrigation	[80], [121], [122], [130]
	Irrigation optimization	[79], [81]–[87], [89], [90], [92], [97], [107], [118], [120], [127], [128], [132], [137], [151]

4.2. Challenges and limitation

Although AI offers significant benefits in agriculture, its implementation faces challenges, especially in developing regions. The effectiveness of AI models can be limited by variable field conditions and poor technological infrastructure, including lack of internet access and specialized equipment [152], [153]. In addition, reliance on large data volumes is problematic where infrastructure cannot support efficient data management. High implementation costs also limit access for smallholder farmers, increasing inequality. The lack of training in AI tools further hinders adoption, highlighting the need for education and support programs. Cultural resistance and preference for traditional methods are additional barriers. Addressing these issues is essential to ensure AI becomes a practical and inclusive tool. Current research must focus on adapting AI solutions to local conditions, as many are designed for broad markets and may not suit specific microclimates or soils. Further studies on AI's potential to support long-term agricultural sustainability particularly in biodiversity and soil health are also critical. Moreover, AI can assist in climate change adaptation, especially in vulnerable regions [154]. These research areas are key to maximizing AI's positive impact and advancing global agricultural sustainability.

4.3. Future directions

Future directions in AI for agriculture should prioritize accessibility and adaptability across diverse environments. Research must focus on models that function with limited data and in challenging conditions, ensuring ease of use for smallholder farmers. Integrating AI with traditional farming practices can support adoption while respecting local customs. Additionally, further study is needed on AI's role in long-term sustainability and the inclusion of small-scale producers-areas still underexplored. Advancing these lines of inquiry will help maximize AI's potential, ensuring equitable, effective, and sustainable benefits for all agricultural communities.

5. CONCLUSION

The systematic literature review on AI applications in agriculture highlights how these technologies are transforming the industry. AI has improved efficiency, sustainability, and productivity in key areas such as crop improvement, irrigation, and pest and disease detection. It has revolutionized decision-making by enabling the customization of agricultural practices based on soil, climate, and crop conditions, resulting in better resource use and reduced phytosanitary risks. Significant impacts are evident in crop management, especially in pest and disease control and crop recommendation using historical and soil data. AI also enables early detection and control of diseases and pests through image analysis, IoT, and sensors, allowing for quick and accurate responses. Moreover, AI supports climate change adaptation by analyzing climatic data and predictive models, helping farmers minimize negative effects. However, challenges remain regarding ethical, economic, and privacy concerns, which must be addressed to ensure equitable access and responsible use. In summary, the systematic review underscores that AI has triggered a profound change in the way food production is grown and managed. The opportunities for improving efficiency, sustainability and resilience in agriculture are abundant and continue to evolve as AI advances and becomes even more integrated into the agricultural industry.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Michael Cabanillas-Carbonell	✓	✓			✓	✓		✓	✓				✓	
Joselyn Zapata-Paulini				✓	✓		✓	✓		✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable.

DATA AVAILABILITY

This study is a systematic review of literature. All data analyzed during this study are derived from previously published sources, which are cited in the manuscript. No new data were generated or collected by the authors for this review.

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