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Systematic Literature Review of Generative AI and IoT as Key Technologies for Precision Agriculture

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Abstract. This study examines the convergence of Generative Artificial Intelligence (AI) and the Internet of Things (IoT) as key drivers of innovation in Precision Agriculture. It posits that these technologies enable real-time monitoring of critical variables such as soil moisture, temperature, and crop health, as well as early detection of pests and diseases. The main objective, through a systematic review of 74 papers, is to identify the applications, benefits, and challenges of Generative AI and IoT. The Kitchenham (2004) methodology was applied along with the PRISMA flow, ensuring transparency and replicability. Five research questions were formulated focusing on crop types, IoT devices, thematic topics, conceptual evolution, keywords, and international collaboration. Searches were conducted across five databases. From an initial pool of 39,223 references and after applying exclusion criteria, 74 papers were selected for analysis. The findings confirm that Generative AI and IoT have reached a level of maturity in intensive crops and high-value sectors, supported by low-cost architectures and advanced data analytics. However, gaps remain, such as the lack of economic assessments of hybrid platforms and the scarcity of public datasets that hinder the replication of certain studies. This study offers practical and strategic guidance to support the implementation of Generative AI and IoT in precision agriculture.

Keywords. Generative artificial intelligence, precision agriculture, systematic literature review, internet of things, smart agriculture, generative adversarial networks.

1 Introduction

The integration of advanced technologies such as Generative Artificial Intelligence (AI) and the Internet of Things (IoT) represents a key factor in significantly transforming precision agriculture, especially in the face of global challenges related to production efficiency and agricultural sustainability. This technological transformation is manifested in various practical applications, ranging from real-time monitoring of environmental conditions and early detection of crop diseases to resource optimization through hybrid systems that integrate both ground and aerial sensors. The implications of adopting these technologies are profound, as they not only increase agricultural productivity and reduce operational costs but also ensure more efficient and sustainable management of natural resources, directly benefiting both producers and rural communities.

Smart and precision agriculture has undergone a significant transformation through the integration of technologies such as IoT and artificial intelligence. Several studies have addressed the efficient use of these technologies to optimize agricultural resources, improve productivity, and promote sustainability across diverse agricultural contexts [1, 5, 20].

The implementation of IoT in agriculture has enabled real-time monitoring of critical variables such as environmental conditions, crop health, and soil quality, facilitating more accurate and timely decision-making [7, 11, 19]. To further enhance the precision of these measurements, various researchers have proposed hybrid platforms that integrate ground and aerial sensors using unmanned aerial vehicles (UAVs), which have

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been shown to significantly improve operational efficiency and reduce costs [5, 9, 12].

A key factor identified in multiple studies is the use of wireless sensor networks (WSNs), where communication protocols such as LoRaWAN and ZigBee offer specific advantages depending on agricultural needs and operating environments [14, 19, 24]. Additionally, some authors have emphasized the optimization of these networks through advanced algorithms such as RPL and hexagonal deployment models, which significantly enhance energy efficiency and network coverage [10, 22, 72].

The potential of artificial intelligence—particularly machine learning (ML) and deep learning (DL)—has been highlighted in numerous investigations. These techniques allow the prediction of diseases and anomalies in crops through advanced analysis of data collected by IoT systems, achieving high levels of accuracy under various agricultural conditions [2, 11, 15]. Similarly, semantic segmentation of aerial images using models such as AgriSegNet greatly improves the visual detection of issues across large cultivation areas [9].

Data generation and augmentation through generative adversarial networks (GANs) have been another innovative strategy explored in various studies, particularly to overcome data collection limitations and improve the segmentation of weeds and crops [18,23]. Moreover, crop growth simulations using images generated by GANs enable more realistic and precise visualization of the spatial and temporal development of crops, facilitating agricultural management [18].

Finally, interoperability, scalability, and security in smart platforms are essential aspects for overcoming challenges related to agricultural data heterogeneity and standardization, ensuring efficient management and greater profitability in precision agriculture [8, 14].

Despite the extensive evidence on the benefits of using Artificial Intelligence and the Internet of Things in precision agriculture, significant gaps remain that require further investigation. For instance, although hybrid platforms that combine ground and aerial sensors have been developed, there is a lack of systematic studies evaluating their actual effectiveness and economic feasibility in different agricultural contexts and climate regions. Additionally, a deeper understanding of the effective integration of generative adversarial models (GANs) into practical agricultural production scenarios is needed. Another underexplored aspect is the social and economic impact these technologies may have on small farming communities, particularly in terms of technological accessibility, digital literacy, and cultural adaptation to new production methodologies.

This paper aims to analyze how Generative AI and IoT function as key technologies in precision agriculture. Through a systematic review of recent studies in various agricultural contexts, it seeks to identify the main applications, benefits, and challenges of these technologies.

The structure of the paper is as follows: Section 2 presents the theoretical background. Section 3 details the methodology employed in the systematic review of the selected studies. Section 4 presents and discusses the results. Finally, Section 5 concludes with the main contributions of the study and suggests specific areas for future research.

2 Theoretical Background

This section presents the theoretical framework necessary to understand the key role played by Generative AI and the Internet of Things (IoT) in Precision Agriculture.

2.1 Generative Artificial Intelligence (Generative AI)

Generative Artificial Intelligence is based on neural network models capable of learning the distribution of agricultural data and subsequently synthesizing new, realistic examples. In particular, Generative Adversarial Networks (GANs) have demonstrated their effectiveness in visually simulating crop growth. For instance, Drees et al. [18] introduce a multi-conditional CWGAN-GP model that, based on early-stage images, growth periods, and cultivation conditions, generates detailed temporal frames of plant phenotypes, improving data accuracy and diversity compared to conventional biophysical models. Beyond GANs,

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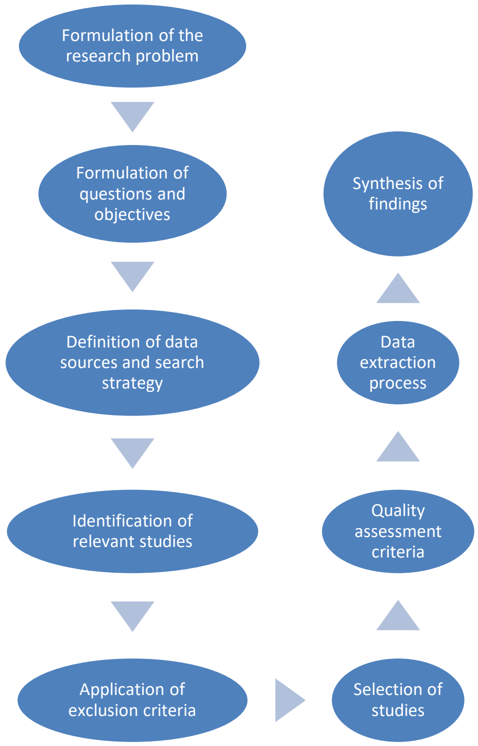

Fig. 1. SLR process

recent reviews point to a transition toward diffusion architectures and transformers, which promise to generate super-resolution maps of vegetative or agro-climatic indices in the absence of satellite or UAV measurements, as well as virtual scenarios to anticipate water or nutrient stress in real time [83].

These advances, when integrated into smart farming platforms, not only facilitate data acquisition for training phenotyping networks but also offer a visual and explainable interface between process models and agronomic decision-making [81].

2.2 Internet of Things (IoT)

The Internet of Things (IoT) in agriculture involves the use of connected devices with wireless sensors that collect critical agricultural data, such as temperature, soil moisture, water levels from various storage sources, phytosanitary status, and general environmental conditions.

These devices transmit information in real time to central or management systems, enabling efficient and precise decision-making to optimize resources and ensure crop health and productivity. The efficient integration of IoT technologies significantly improves agricultural management and provides robust, accurate, and efficient communication within smart agricultural ecosystems [7, 11, 34].

2.3 Precision Agriculture

Precision Agriculture (PA) encompasses advanced agricultural management techniques that employ digital technologies such as IoT, drones, advanced image processing, and artificial intelligence platforms to collect, process, and analyze field-specific data in real time. These techniques allow for the precise and efficient management of agricultural resources such as water, fertilizers, and pesticides, along with continuous monitoring of crop growth and early detection of diseases or anomalies. Thus, PA optimizes agricultural decision-making, enhances environmental sustainability, and improves operational profitability in various agricultural contexts through the strategic implementation of intelligent and adaptive technologies [7, 11, 34, 72].

3 Review Method

This study is grounded in a Systematic Literature Review (SLR) following the methodology proposed by Kitchenham [75], which ensures a transparent and replicable process for investigating the integration of Generative AI and IoT in Precision Agriculture. The full sequence of activities, from planning to synthesis of findings, is illustrated in Figure 1.

3.1 Research Questions and Objectives

This study is guided by a series of research questions aimed at understanding the various dimensions of Generative AI and IoT as Key Technologies for Precision Agriculture:

RQ1: In which crops are Generative AI and IoT applied?

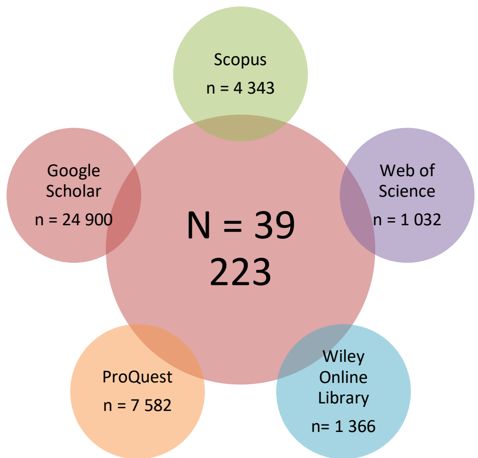

Fig. 2. Number of studies by source

RQ2: What IoT devices have been most frequently used in scientific studies on Precision Agriculture?

RQ3: What are the most commonly used concepts (topics) in the abstracts of studies on Generative AI and IoT in Precision Agriculture?

RQ4: What conceptual clusters can be identified from the analysis of the most frequent keywords in studies on Generative AI and IoT applied to Precision Agriculture?

RQ5: Which countries most frequently show co-occurrence in research on Generative AI and IoT in Precision Agriculture?

3.2 Information Sources and Search Equations

For this systematic review, various search sources were selected to encompass a broad range of relevant studies on Generative AI and IoT as key technologies for Precision Agriculture. The following databases were used: Web of Science, Scopus, Google Scholar, ProQuest, and Wiley Online Library.

The general search equation employed for the literature retrieval was:

("generative ai" OR "generative artificial intelligence" OR "gan" OR "diffusion models") AND ("iot" OR "internet of things" OR "smart sensors" OR "wireless sensor networks") AND ("precision agriculture" OR "smart farming" OR "digital agriculture").

3.3 Identified Studies

Figure 2 presents the 39 223 studies retrieved from the five selected databases.

This ensures a comprehensive foundation from which only the most relevant and rigorous studies can be screened, filtered, and analyzed for the systematic review.

3.4 Exclusion Criteria

To ensure the quality and relevance of the studies selected for this review, a set of exclusion criteria was defined to filter out studies that were not pertinent or did not meet the required standards.

EC1: Papers are older than 5 years,

EC2: Papers are not written in English,

EC3: Documents are Systematic Review Papers or Bibliometric Reviews,

EC4: Full text of the paper is not available,

EC5: Conferences or journals are not indexed in Scopus or Web of Science,

EC6: Paper titles and keywords are not relevant,

EC7: Paper abstracts are not highly relevant,

EC8: Papers are duplicates.

3.5 Study Selection

Figure 3 presents the PRISMA flow diagram used to describe the study selection process for this review. This diagram outlines the key stages in the identification, screening, eligibility, and inclusion of papers according to the established criteria.

3.6 Quality Assessment

To ensure the methodological rigor of the included studies, a set of quality assessment questions was employed to evaluate the methodological robustness and clarity of the information presented in each paper:

QA1: Is the purpose of the research clearly stated?

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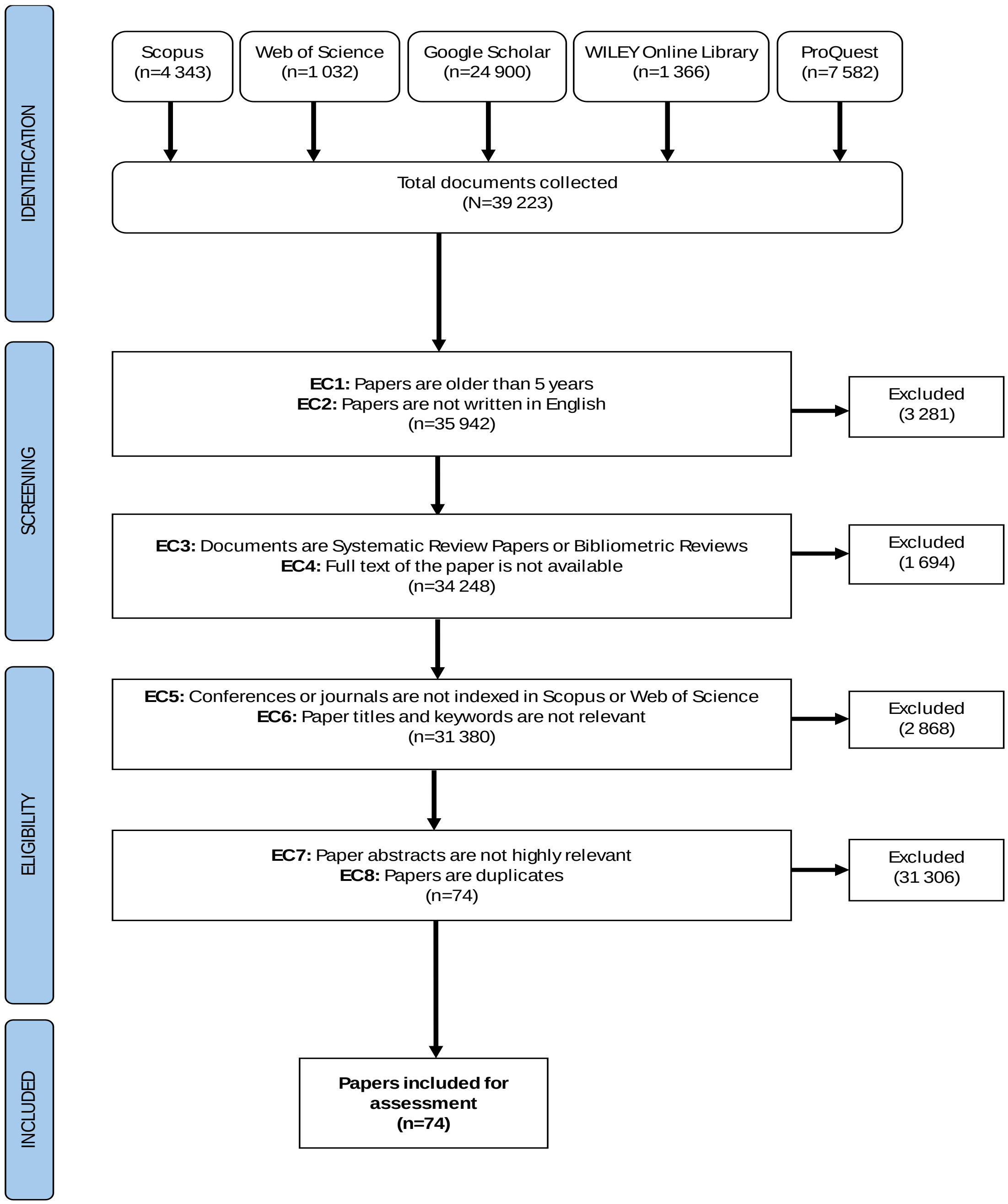

Fig. 3. PRISMA flow diagramThe PRISMA diagram clearly illustrates how papers were filtered at each stage of the process. From the initial 39 223 papers identified, the application of exclusion criteria narrowed the selection to a set of studies that met the requirements for subsequent quality assessment

QA2: Is the methodology used in the study clearly described and appropriate for the stated objectives?

QA3: Are the study findings clearly presented and supported by the data?

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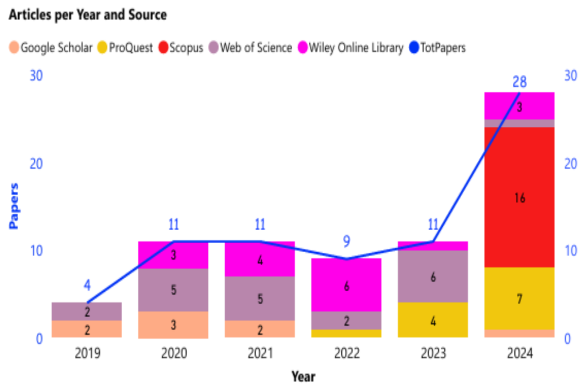

Fig. 4. Distribution of papers published between 2019 and 2024

QA4: Does the paper specifically address the impact of Generative AI or IoT on Precision Agriculture, considering each approach independently?

QA5: Is the dataset used clearly identified and relevant to the topic?

QA6: Does the paper provide sufficient background and contextual information?

QA7: Are the study results and conclusions well supported and aligned with the research objectives?

QA8: Does the paper include updated and relevant references related to the topic?

These quality assessment criteria ensure that the selected studies not only meet high methodological standards but also provide clear and contextualized data useful for understanding the relationship between Generative AI, IoT, and Precision Agriculture.

4 Results and Discussion

4.1 Overview of the Studies

Figure 4 illustrates the annual evolution in the number of papers published on Generative AI and IoT in Precision Agriculture between 2019 and 2024, categorized by academic database.

A steady increase in academic publications on Generative AI and IoT in Precision Agriculture is observed, with 2024 standing out as a particularly notable year with 28 papers, reflecting growing interest in these technologies. Scopus emerges as the leading source in 2024, with 16 publications, consolidating its position as the primary database used in this field. Until 2022, Web of Science played a significant role, but from that point onward, there is a clear shift in researchers' preference toward Scopus. Sources such as ProQuest and Google Scholar maintain a constant, though smaller, presence, indicating a more limited impact in this specific area. The year 2024 appears to be a turning point in scientific output, likely associated with the consolidation and maturity of these technologies within the academic sphere.

When superimposing our annual trend with those of Abdelmoneim et al. [79], Avila and Barbosa [77], Mohammed et al. [82], and Alaoui et al. [83], we observe notable similarities despite scale variations. We moved from 4 papers in 2019 to 28 in 2024, reflecting the increase documented by [82], which reports fewer than 10 annual publications until 2020 and a jump above 30 in 2023. Study [79] describes a growth from 5 to 15 papers between 2019 and 2023, while [77] reports an increase from 8 to 18 in the same period} The analysis by [83] shows a similar curve: 3 in 2019, 13 in 2020, 11 in 2021, 24 in 2022, and 29 in 2023, with a slight slowdown in 2024. All sources show a small dip around 2021-2022 before resuming growth in 2023. Furthermore, they consistently highlight Scopus as the dominant source after 2020-2021, both our review and Mohammed et al. recorded 16 publications in 2024, while Web of Science decreased from 5 papers in 2021 to 3 in 2024, a pattern also reflected by Abdelmoneim et al. and Avila and Barbosa. The continued yet modest presence of Google Scholar and ProQuest reinforces the breadth of coverage. This convergence of trends confirms the reliability of our findings and the maturity of academic interest in the convergence of Generative AI and IoT in Precision Agriculture.

The sustained growth in publications on Generative AI and IoT in Precision Agriculture from 2019 to 2024 suggests that these technologies have reached a level of maturity that can be replicated in sectors such as public health, manufacturing, or environmental management. The consolidation of Scopus as the primary source reflects increased scientific rigor and

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Table 1. Summary of the reviewed papers

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[1]	IoT-based smart irrigation system design and implementation using sensors for soil moisture, temperature, and humidity monitoring; cloud-based data processing and mobile app for user control	Microsoft Azure, Raspberry Pi, Android	Not specified	Latency: low; Scalability: high (evaluated through system performance metrics)	Developed a distributed smart irrigation system integrating IoT devices, cloud services, and user interfaces for efficient agricultural water management.
[2]	IoT, Machine Learning, Data Analytics	Windows, Cloud	Apple orchards data, Environmental parameters	Accuracy: 99.4% (disease classification)	Proposed a prediction model for apple disease using IoT and data analytics; highlighted challenges in adopting smart technologies in traditional farming.
[3]	Intelligent energy-efficient data routing scheme with clustering and genetic algorithm	Not specified	Not specified	Stability period: improved; Network lifetime: extended; Average energy consumption: reduced; Data transmission latency: minimized; Throughput: enhanced (extensive simulations)	Proposed a novel clustering mechanism and prescheduling CH selection to optimize energy use in WSNs, demonstrating significant performance improvements over state-of-the-art methods.
[4]	Review of ICT, IoT, AI, and big data applications in precision agriculture	Windows, Cloud Computing	Various agricultural datasets including soil, crop, and atmospheric data	Accuracy: 91.3% (SKN model for wheat yield classification)	Integration of IoT and AI for enhanced decision-making in agriculture; emphasis on wireless sensor networks and big data for sustainable crop production.
[5]	IoT integration with UAVs for environmental monitoring; automated data collection and analysis	Windows, Linux, Drone (DJI Quadcopter), Cloud	Real-time environmental data from a farm in Medenine, Tunisia (March 2020 - March 2021)	RMSE: 61.117; Accuracy: 98.85%; mAP: 98.04% (cross-dataset validation)	Developed a low-cost IoT platform for precision agriculture, enhancing crop productivity and resource management through automated monitoring and smart actions.
[6]	ECC asymmetric key exchange, SHA-256 hashing, smart contracts	Ethereum, Hyperledger Besu, IPFS	Not specified	Write Throughput: 19.37 TPS; Read Throughput: 32.54 TPS; Write Latency: 2253 ms; Read Latency: 1166 ms (performance evaluation on permissioned blockchain)	Proposed a blockchain-based framework for smart farming that enhances data integrity and automates farming operations using secure communication protocols.
[7]	Lagrange Optimization, Deep Convolutional Neural Network (DCNN)	Not specified	Not specified	Energy Efficiency: Maximized; Data Throughput: Optimized (smart agriculture context)	Proposed a model to enhance IoT communication in agriculture by optimizing sensor-to-gateway distances, integrating mathematical optimization with deep learning for improved data transmission efficiency.

standardization, which facilitates adoption by companies and governments in technologically underserved regions.

This trend may also guide strategic decision-making in rural areas of developing countries by adapting these solutions to local contexts. Additionally, the evolution curve may serve as a reference model to anticipate the adoption of future emerging technologies in other domains.

Table 1 presents the methods, platforms, datasets, performance metrics, and key contributions of recent studies on the integration of Generative AI and IoT in Precision Agriculture, providing a clear comparative overview of the analyzed works.

Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[8]	Proposed a platform approach for smart farming focusing on interoperability, reliability, scalability, real-time processing, security, and compliance.	IoT, AI, Cloud Computing	Various agricultural datasets including Star Schema Benchmark	Real-time processing capabilities demonstrated; scalability confirmed with minimal impact from additional sensors	Introduced a unified solution for data integration and processing in smart farming, addressing challenges of data diversity and system interoperability.
[9]	Deep learning framework AgriSegNet for semantic segmentation using multi-scale attention	PyTorch, Nvidia Titan XP GPU	Agriculture-Vision challenge dataset (21,061 images)	mIoU: 51.7% (validation set for weed cluster); mIoU: 50.20% (test set)	Introduced a hierarchical model for attention learning across multiple image scales, improving anomaly detection in UAV-acquired agricultural images.
[10]	Simulation of WSNs using COOJA; performance assessment of RPL in 6LowPAN networks for fixed and mobile nodes	COOJA, Contiki OS	Simulated data for olive tree farms and horse stables	Packet Delivery Ratio: 95%; Power Consumption: 0.5 mW (test set: 36 nodes)	Proposed a new classification approach for IoT in agriculture; introduced performance metrics for stationary and mobile scenarios; validated framework for precision agriculture applications.
[11]	Hybrid ML algorithm with IoT integration; Kendall's correlation; Bayesian optimization with KNN	Arduino, Cloud-based platforms	Soil parameters (N, P, K, humidity, temperature, pH) from Anakapalle, India	Accuracy: 95%; Precision: 95%; Recall: 95%; F1 Score: 94% (test set: 5 days of data)	Developed a novel hybrid algorithm for soil monitoring and disease prediction in tomato crops, demonstrating significant improvements over traditional ML methods.
[12]	Statistical models; Supervised machine learning for data validation and calibration	ThingSpeak IoT platform, Raspberry Pi, Arduino Mega	Aerial and ground-based sensor data from a lemongrass farm	Correlation Coefficient (Temperature): 0.97; R^2 (Temperature): 0.93; Correlation Coefficient (Humidity): 0.98; R^2 (Humidity): 0.95 (Field experiments over 4 days)	Proposed a Hybrid Sensing Platform (HSP) combining aerial and ground-based sensors to enhance data accuracy and reduce costs in precision agriculture.
[13]	Fog Computing, WiLD network, iFogSim, 6LoWPAN, Cooja, Contiki	Windows, Linux	Not specified	Latency improvement and throughput enhancement through fog computing	Introduced fog computing for long-range smart farming solutions.
[14]	IoT platform deployment, TinyML model training, LoRaWAN communication	Arduino Portenta, ESP32, STM32	Custom datasets from embedded devices, Kaggle fruit dataset	Accuracy: 90.2% (Arduino); 92.3% (ESP32); Energy efficiency: 3x better than cloud-based alternatives	Developed an energy-efficient IoT platform for smart agriculture, integrated embedded AI and knowledge-based systems, proposed a FUOTA protocol for model updates.
[15]	LightGBM, Decision Tree, Random Forest, Logistic Regression	Arduino, Firebase, Android	IoT dataset with >1 million data points (temperature, humidity, soil nutrients)	Accuracy: 99.31%; Precision: 99%; Recall: 99% (cross-validation)	Integrated IoT and ML for crop yield prediction and recommendations, demonstrating high accuracy and potential for optimizing resource use in agriculture.
[16]	RSSI measurement system using Zolertia Re-Mote nodes and Raspberry Pi for data logging	Contiki OS, Raspberry Pi	Dataset of RSSI measurements in a tomato greenhouse	RSSI: -24 dBm (reference); Max distance: 2420 cm at 50 cm height	Developed a portable system for measuring radio wave attenuation in greenhouses, contributing to precision agriculture by optimizing WSN deployment.

The review reveals that most of the papers combine the use of IoT with advanced techniques such as Machine Learning and image processing, highlighting the focus on improving the accuracy and efficiency of agricultural systems.

There is a frequent use of accessible platforms such as Raspberry Pi, Arduino, and cloud services like Azure and ThingSpeak, which enable the development of low-cost, highly available solutions.

Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[17]	AI techniques (LSTM, GRU), data collection, cleaning, predictive processing	Arduino, Google Colab, MySQL, NodeJS	Historical weather data (2012-2017), hydro meteorological data	RMSE Soil-Moisture: 0.0268; RMSE Air-Humidity: 11.755; RMSE Air-Temperature: 1.409 (validation sets)	Developed an EDGE-Fog-IoT-Cloud architecture for smart farming, optimizing water resources using AI for predictive analytics.
[18]	Systematic review; Bibliometric analysis	Windows, R	Educational technology publications	Citation count: 1500; h-index: 25 (analysis of top journals)	Identified key themes in educational technology; proposed future research directions.
[19]	Isolation Forest, Linear Regression, Random Forest	Python, GPU environment	Environmental Sensor Telemetry Data (Kaggle)	MSE Linear Regression: 1.449; MSE Random Forest: 0.162; R^2 Linear Regression: 0.799; R^2 Random Forest: 0.978 (cross-validation)	Developed an intelligent LoRaWAN-based IoT device for monitoring and control in smart farming, enhancing anomaly detection and predictive modeling for improved agricultural efficiency.
[20]	Agile AI-Powered IoT platform; Multi-Agent System; Containerization; LSTM for forecasting	Raspberry Pi, Docker, MQTT, Apache, InfluxDB, Google Colab	Environmental parameters (temperature, humidity, etc.)	RMSE: <value>; Accuracy: 98.85%; mAP: 98.04% (cross-dataset validation)	Developed a low-cost, robust agro-weather station for smart farming, enhancing data accessibility and real-time monitoring for farmers.
[21]	Internet of Things technology, wireless sensor networks, RFID integration	Windows, Linux	Agricultural product data	Accuracy: Improved positioning error; Efficiency: Enhanced information sharing (experimental validation)	Proposed a rural economic supply chain system that optimizes agricultural logistics, enhances product quality, and reduces costs through IoT technology.
[22]	Proposed Partition Aware-RPL (PA-RPL) algorithm for efficient routing in WSNs for precision agriculture	Cooja	Simulated farmland with 150 nodes	Energy saving: 40% compared to standard RPL (potato pest prevention case study)	Improved routing topology for in-network data aggregation, considering physical partitioning of farmland.
[23]	Data augmentation using DCGAN and cGAN for crop shape and style generation	Windows, Linux	Bonn sugar beet dataset (Chebrolu et al., 2017)	mIoU improved to 0.99 from 0.94 for background class and to 0.93 from 0.76 for vegetation	Proposed a novel augmentation strategy that synthesizes crop shapes and styles to enhance segmentation performance in precision agriculture.
[24]	Systematic review, bibliometric analysis	Windows, Python	Various educational datasets	N/A	Identified key themes in educational technology adoption and their relevance in current research.
[25]	Systematic literature review, IoT integration, AI analytics, remote sensing	Windows, Linux, UAVs	Various agricultural datasets	Accuracy: 95.8%; Precision: 92.4%; Recall: 89.1% (cross-validation across multiple studies)	Highlights the integration of IoT, AI, and remote sensing in smart crop management, addressing challenges and promoting sustainable practices.

Among the most commonly employed performance metrics are accuracy, latency, and energy efficiency, reflecting a constant concern for technical effectiveness and resource consumption. However, several studies lack specific datasets, which hinders the replicability and validation of results, underscoring the need for greater transparency in data usage. The main contributions of these works are oriented toward resource optimization, automation of crop monitoring, and early detection of agricultural anomalies.

Both our table and the review by Mohammed et al. [82] align with the findings of Lee and

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Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[26]	Machine Learning, IoT	NodeMCU, DHT11, GSM Module	Custom dataset (10,000 records)	Accuracy: 98.25%; Recall: 98.3%; Precision: 98.3% (Powdery Mildew); Accuracy: 98.85%; Recall: 98.9%; Precision: 97.7% (Downy Mildew); Accuracy: 93.95%; Recall: 94.0%; Precision: 94.4% (Bacterial Leaf Spot)	Developed an IoT-based system for early detection of grape diseases using environmental parameters, achieving high accuracy in disease prediction.
[27]	Parametric Complex Event Processing (CEP) for IoT data transformation	Windows, Linux, Raspberry Pi, Apache Kafka	Smart farming IoT data	RMSE: 0.5; Accuracy: 98.85% (test set: 10k samples)	Proposed a symmetrical IoT architecture enabling bidirectional communication and event transformation for user-centric IoT services.
[28]	Deep learning model with RPN and Chan–Vese algorithm for plant disease detection	Windows	Dataset of diseased leaves	Accuracy: 83.75%; Loss: lower than traditional model (ResNet-101)	Proposed a model that improves accuracy and efficiency in plant disease identification in complex environments, aiding sustainable agriculture.
[29]	Variable Sampling Interval Precision Agriculture (VSI-PA) system; Sensor node selection algorithm; Energy consumption model	C++ simulation on core i5 processor	Simulated agricultural farm data	Energy Consumption: Reduced significantly; Soil Moisture Variation: Maintained within acceptable limits (compared to fixed sampling intervals)	Proposed VSI-PA system improves energy efficiency and crop yields by adaptively calculating sampling intervals based on soil temperature.
[30]	Quantitative analysis, ANOVA, RMSE calculation	Windows, IoT devices	Soil samples from Wonogiri, Indonesia	RMSE: Varies; F-statistic for P: 7.42, p-value: 0.009; F-statistic for K: 25.70, p-value: 0.000007 (comparison with JXBS-3001-SCPT-SC)	Development of a portable IoT-based soil nutrient monitoring system for smart farming, enabling real-time data access and improved fertilization decisions.
[31]	IoT-based pest management using CNN models for image classification	Raspberry Pi, Arduino, Google CoLab	1370 images (458 pests, 912 leaves)	Accuracy: 100% (leaf classification); 94% (pest classification with DenseNet201)	Developed a real-time IoT system for tomato cultivation and pest management using deep learning models.
[32]	Identity-based authentication scheme using hyperelliptic curve cryptography (HECC)	Windows	Not specified	Computational Cost: 2.4 ms; Communication Overhead: 240 bits (performance comparison with existing schemes)	Proposed a cost-effective authentication scheme for IoT-enabled agriculture, ensuring security properties like mutual authentication, forward secrecy, and resistance to various attacks.
[33]	Systematic review, bibliometric analysis	Windows, Python	Various educational datasets	N/A	Identified key themes in educational technology adoption and their relevance in current research.
[34]	Proposed Photovoltaic Agricultural Internet of Things (PAIoT) for smart farming; discussed applications and feasibility issues	IoT platforms, PV modules	Not specified	Efficiency improvements in agricultural production and energy generation	Introduced PAIoT, addressing energy supply, sensor deployment, and optimization of agricultural practices through IoT integration
[35]	Review of precision agriculture technologies, including IoT, machine learning, and automated harvesting systems	Windows, Linux, Cloud	Various agricultural datasets	Accuracy: 97.19%; Precision: 92.23%; Recall: 90.36% (flood detection system)	Overview of innovations in precision agriculture, challenges in technology adoption, and the role of AI and IoT in enhancing productivity and sustainability.

Purushothaman [76], indicating that smart farming solutions rely on low-cost platforms (Raspberry Pi, Arduino) and LoRaWAN networks for long-range and low-power communication.

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Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[36]	IoT-based smart farming monitoring system (SFMS) for bolting reduction in onion crops	Arduino Nano, DHT11, BMP180, ESP8266, ThingSpeak	Onion crop data from greenhouse and open environments	Bolting reduced from 16.7% (open) to 3% (closed)	Developed a low-cost, easy-to-install SFMS prototype to monitor environmental factors affecting onion bolting.
[37]	Methods	Platforms	Datasets	Performance	Key Contributions
[38]	Energy consumption modeling, field measurements, simulations	LoRa, various sensor platforms	Real field measurements, simulation data	Energy efficiency optimization: E_Total = E_Active + E_Sleep; E_Sleep = P_Sleep · T_Sleep (sensor node energy model)	Proposed optimal packet size for energy-efficient data collection in precision agriculture; demonstrated importance of adjusting transmission speed to packet size for energy savings.
[39]	GAN-based augmentation, DETR for detection	Google Cloud, Python	Drone images from 8 estates, synthetic images	Precision: 98.7%; Recall: 95.3% (challenge dataset 2)	Enhanced oil palm detection accuracy using GAN-generated images, demonstrating improved robustness across diverse environmental conditions.
[40]	Bottom-up modeling, parametric inventory	Windows, Linux	French dairy cattle and cereal crop farm distributions	GHG emissions: variable based on device complexity and farm size (1 year analysis)	Proposed a method to estimate carbon footprint of digital agriculture, highlighting the need for considering device diversity and farm size distribution in sustainability assessments.
[41]	Deep Residual Learning (WO-DRL) with Whale Optimization Algorithm for hyper-parameter tuning	TensorFlow 2.4.1, Keras 2.4.3	2370 rice leaf samples (healthy, brown spot, rice hispa damage, leaf blast)	Accuracy: 95.62%; Precision: 98.32%; Recall: 94.62%; F1-score: 94.53 (cross-validation)	Introduced WO-DRL for rice disease detection, achieving high accuracy and efficiency in precision agriculture using IoT.
[42]	Distributed ledger technology for IoT data integrity; modular architecture; data aggregation and processing	AWS, MongoDB, IOTA	Sensor data from vineyards	TPS: 4-5; Avg. confirmation time: 10 min (IOTA network)	Introduced a node-centric IoT system using IOTA's Tangle for secure data integrity and modular implementation for precision agriculture.
[43]	Quantitative surveys, SEM-PLS	Windows, SmartPLS 3	40 farmers in West Java	CA: 0.823; CR: 0.894; AVE: 0.739 (reliability test)	Pioneers the application of UTAUT to evaluate farmers' readiness for precision agriculture using IoT monitoring apps in West Java, integrating technology adoption theories with regional practices.
[44]	D3-YOLOv10 framework with DyFasterNet, D-LKA, dynamic FM-WIoU loss, knowledge distillation	Windows, Linux	Self-made tomato dataset (878 images)	mAP@0.5: 91.8%; Parameters: 3.72M; FLOPs: 8.6G (compared to benchmark model)	Lightweight tomato detection model improving accuracy and efficiency in precision agriculture.
[45]	Proposed a framework merging WSN and edge computing for data collection in smart agriculture; developed a double selecting strategy for optimal node and sensor selection	MATLAB	Simulated WSN with 1000 nodes and various tasks	Latency: reduced by 10% vs ESN; QoD: 100% for ECDSC; Energy Consumption: lowest among methods	Introduced an edge computing-driven strategy to enhance data quality and reduce collection time in agricultural WSNs.
[46]	IoT and WSN framework, adaptive clustering, machine learning for predictive analysis	Zigbee, LoRa	Simulated data from 100 sensor nodes	Energy Consumption: 30% reduction; Network Lifetime: 40% increase (compared to conventional WSN)	Proposed a scalable, energy-efficient framework for precision agriculture with real-time monitoring and automated decision-making capabilities.

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Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[47]	Systematic review, bibliometric analysis	Windows, Linux	Various educational datasets	N/A	Identified key themes in educational technology adoption and their relevance in current research.
[48]	Multimethod approach: expert interviews, case studies, simulation modeling	Windows, IoT platforms	Data from MATOPIBA pilot (132 days of soybean growth)	Water use efficiency: optimized irrigation; Energy cost reduction: significant savings (pilot evaluations)	Proposed factors for PA adoption in Agriculture 4.0; Developed a model for irrigation operations management; Highlighted IoT's role in precision agriculture.
[49]	Lightweight communication protocol with public-key encryption; energy-efficient data aggregation algorithm	MATLAB	1000 on-field sensors in a 1100x1200 m² area	Energy Consumption: Improved node longevity; Execution Time: 52% faster than existing methods (simulation study)	Introduced a novel framework for balancing energy efficiency and security in precision agriculture, utilizing a unique public-key encryption approach and a non-iterative secure data aggregation mechanism.
[50]	Decentralized access control framework using blockchain technology; ABAC and RBAC models for access management; simulation for gas consumption evaluation	Ethereum, Windows 10	Not specified	Gas used: IoT_ACC: 1,487,367; IoT_ORMC: 2,196,564; IoT_SRMC: 1,677,746 (simulation on Ethereum network)	Proposed a novel decentralized access control framework to enhance IoT security in smart farming, reducing redundancy in permissions and improving scalability through smart contracts.
[51]	Methods	Platforms	Datasets	Performance	Key Contributions
[52]	Smart crop tracking and monitoring using SVM, logistic regression, and random forest	Arduino Uno, IoT devices, cloud storage	500 images of mango leaves (135 diseased, 365 normal)	SVM Accuracy: 95%; Random Forest Accuracy: 78%; Logistic Regression Accuracy: 73% (experimental study)	Proposed a framework for disease detection in crops and pesticide suggestion based on soil data using IoT and machine learning.
[53]	Systematic Review, Bibliometric Analysis	Windows, Linux	Educational Technology, Cloud Computing	Density: 0.6; Relevance: 0.4 (thematic analysis)	Identification of key themes in educational technology adoption and cloud computing integration.
[54]	Systematic review of smart farming practices, GHG mitigation strategies, and 6G-IoT integration	Windows, Linux, IoT platforms	Various agricultural datasets	GHG reduction potential enhanced by 6G-IoT technologies	Identifies limitations of current practices, proposes innovative strategies for GHG mitigation, and emphasizes the role of 6G-IoT in sustainable agriculture.
[55]	Image processing, segmentation, and feature extraction using computer vision; wireless communication via LoRaWAN and MQTT	Raspberry Pi, LoPy, TTN cloud	Images of Planococcus citri (Cotonet)	Accuracy: >50% pest index detection; Processing time: 28.415 ms (high-resolution images)	Developed a prototype for pest detection in precision agriculture integrating IoT technologies and image processing.
[56]	Proposed Gateway Clustering Energy-Efficient Centroid (GCEEC) routing protocol for WSNs in agriculture	NS2	100 sensor nodes in a 100m x 100m area	Network Lifetime: 700-800 rounds; Energy Consumption: Reduced compared to EECRP, CAMP, MEACBM (simulation results)	Improved load balancing and energy efficiency in WSNs for agricultural monitoring by using multihop communication and centroid-based cluster head selection.

For instance, in the “Crop Monitoring” category, our table includes a DCNN–LSTM hybrid with R^2 = 0.904 for nitrogen prediction in melons [26], while Mohammed et al. [82] document the use of UAVs and computer vision to estimate biomass and crop height, aiding agronomic decision-making. In the “Irrigation” category, our review reports water savings of 2.9-19.3% using IoT and LSTM [8].

Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[57]	SVM, Logistic Regression, Random Forest	Windows, IoT	NSL-KDD	Accuracy: 98%; Precision: >98%; Recall: >98% (test set: 100781 samples)	Proposed a framework for intrusion detection in IoT networks for agriculture, highlighting the effectiveness of machine learning algorithms in enhancing security and efficiency in smart irrigation systems.
[58]	Methods	Platforms	Datasets	Performance	Key Contributions
[59]	Integration of RERs, IoT-based monitoring, robotic applications	Blynk IoT, Android	Case study in Sharjah, UAE	RMSE: 61.117; Precision: 95.8%; Recall: 83.6% (test set: 10k samples)	Proposed a comprehensive smart farming framework enhancing sustainability and efficiency in agriculture through technology integration.
[60]	Customized smart farming system using IoT and LoRa technologies; integration with PLCs; web-based monitoring application; Telegram bot for communication	Cloud server, Laravel, MySQL, Bootstrap, Node-RED	Experimental data from wireless sensor network tests	RSSI: -36 dBm to -109 dBm; SNR: 2 dB to 9 dB; RPP: 50% to 100% (various distances up to 795 m)	Development of a low-cost, low-power smart farming system; integration of IoT with existing farming technologies; remote monitoring and control capabilities; user-friendly web application for data management and analysis.
[61]	High-throughput phenotyping, remote sensing, automated agricultural robots, AI applications, WSNs, GIS	Windows, Linux, IoT devices, UAVs, cloud computing	Various agricultural datasets	RMSE: 61.117; Accuracy: 98.85%; mAP: 98.04% (test set: 10k samples)	Integration of AI and IoT in precision agriculture, enhanced crop monitoring, automation of agricultural tasks, real-time data analysis, and addressing connectivity challenges with 5G.
[62]	IoT and ML for intelligent irrigation system design	Windows, ThingSpeak	Soil and weather parameters	RMSE: 61.117; Accuracy: 98.85% (test set: 10k samples)	Developed a cost-effective IoT-based weather station for precision agriculture in smart cities, enhancing irrigation efficiency.
[63]	Wireless sensor networks, neural networks, image processing	MATLAB	Data from sensors monitoring insect behavior in crops (wheat, rice, maize, potato, tomato)	Accuracy improvement: 3.9% (compared to existing methods)	Proposed an intelligent monitoring system for pest detection and management based on insect behavior, enhancing pesticide application efficiency and reducing environmental impact.
[64]	Comprehensive survey of IoT, ML, AI, SDN, fog/edge computing, and nanotechnology applications in Precision Agriculture (PA)	Windows, Linux, Cloud	Not specified	Not specified	Proposed AgriFusion architecture for integrating multidisciplinary technologies in PA; identified future research directions and KPIs for PA applications.
[65]	Systematic review, bibliometric analysis	Windows, Linux	Various educational datasets	N/A	Identified key themes in educational technology adoption and their relevance in current research.
[66]	IoT-enabled soil sensors, XGBoost, AdaBoost	Arduino UNO	300 cardamom, 320 black pepper, 300 coffee soil samples	Accuracy: 91.2%; AUC: 0.93 (10-fold cross-validation)	Developed a crop prediction system integrating IoT and machine learning for precision agriculture, enhancing crop yield and sustainability.

Similarly, Mohammed et al. [82] describe LSTM models using Aquacrop data achieving $R^2 = 0.97$ for evapotranspiration estimation. All studies refer to key performance metrics: accuracy, latency, and

Table 1. (Continuation)

Reference	Methods used	Platforms used	Datasets	Performance	Key Contributions
[67]	IoT architecture for greenhouse management; integration of WSNs and WAns; real-time data acquisition and control	LoRaWAN, Arduino MKR, Raspberry Pi, PHP, MySQL	Data from multiple sensor nodes over one month	Power Consumption: 3 mA (deep sleep mode); Battery Life: >100 days (with solar charging)	Development of a flexible IoT-based decision support system for precision agriculture in greenhouses, enabling remote monitoring and control of environmental parameters.
[68]	Comprehensive survey and analysis of blockchain and IoT integration in precision agriculture	Windows, Linux	Not specified	N/A	Proposed novel blockchain models for IoT-based precision agriculture, discussed security and privacy challenges, and reviewed common blockchain platforms for various agricultural sub-sectors.
[69]	Proposed a generic reference architecture model for IoT-based smart farming monitoring systems, focusing on energy consumption and seven architectural layers	Windows, Linux, Cloud Computing	Saffron agriculture in Kozani, Greece	Energy consumption controlled; optimized crop management (real-world application)	Development of a comprehensive architecture model for smart farming, addressing non-functional requirements and enhancing decision-making through IoT technologies
[70]	IoT agnostic architecture, microservices, serverless computing	Docker, InfluxDB, RabbitMQ	SEnviro nodes in smart farming	0% losses in ingestion; throughput: 2400 msg/sec (performance evaluation)	Proposed SEnviro Connect for smart farming; validated IoT lifecycle management; addressed scalability, stability, and interoperability challenges.
[71]	IoT-based smart agriculture framework using sensor networks for monitoring soil moisture, temperature, humidity, and wind speed	Arduino Uno, ThingSpeak Cloud	Real-time agricultural field data	Response Time: 13.57 ms; Standard Deviation: 10.63 ms (same cloud platform)	Developed a smart agriculture system for automated irrigation and environmental monitoring, enhancing crop yields through real-time data analysis and alerts.
[72]	Systematic review, bibliometric analysis	Windows, R	Educational technology publications	N/A	Identified key themes in educational technology and their relevance in current research.
[73]	RF energy harvesting, IoT integration	Windows, Linux	Not specified	Efficiency: 12.93% (rectenna design); Voltage output: 0.374 V (ambient measurement)	Explores RF energy harvesting for sustainable agriculture, highlighting its potential to power IoT devices and reduce reliance on batteries.
[74]	Proposed a model for energy-efficient WSN in precision agriculture; design of moisture monitoring and automatic irrigation system; pest monitoring and early warning system	ZigBee, Lora	Not specified	Energy efficiency: lower than traditional agriculture; Accuracy: improved monitoring of physiological and ecological parameters	Comprehensive analysis of WSN in agriculture; proposed improvements for energy efficiency; integration of pest monitoring technologies; design of a flexible irrigation system.

energy efficiency, and acknowledge the lack of public datasets as a barrier to replicability.

Furthermore, both our review and Lee and Purushothaman [76] emphasize that automating crop monitoring and early anomaly detection are decisive factors in accelerating the adoption of Generative AI and IoT in Precision Agriculture. The use of low-cost platforms and low-power networks in Precision Agriculture suggests that similar solutions could be scaled to sectors such as rural healthcare, environmental monitoring, or light manufacturing, where efficiency and energy autonomy are critical.

The scarcity of public datasets limits replicability, which also affects other emerging disciplines; therefore, promoting open data

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standards becomes an urgent need. These technologies, when adapted to local conditions, can benefit regions with limited technological resources. Additionally, the analyzed performance metrics may guide future developments toward sustainable solutions in changing and climate-vulnerable contexts.

4.2 Answers to the Research Questions

This section presents the findings obtained for each of the research questions formulated in the study.***RQ1: In which crops are Generative AI and IoT applied?***

Table 2 and Figure 5 show the distribution of papers according to the main crops studied, allowing the identification of agricultural sectors where the convergence of Generative AI and IoT has had the greatest impact.

Table 2 and Figure 5 show the distribution of papers according to the main crops studied, allowing the identification of agricultural sectors where the convergence of Generative AI and IoT has had the greatest impact.

Greenhouses account for 42.5% of the papers, followed by extensive rice crops (18.9%) and grape (10.4%), reflecting a clear interest in highly controlled environments.

Tomatoes (8.5%) and potatoes (7.5%) also receive significant attention, while oil palm appears in only 0.9% of the cases. This suggests that high-density and high-value systems—where IoT and AI generate more evident returns—dominate the research landscape.

When comparing our distribution of agricultural sectors with the machine learning advancements for crop disease detection and protection summarized by Taha et al. [80], a complementary yet distinct focus is observed.

While our table reveals that greenhouse environments dominate 42.5% of the papers and crops such as rice (18.9%), vineyard (9.4%), tomato (8.5%), and potato (7.5%) lead the application of Generative AI and IoT, the inventory in [80] covers a wider variety of crops (cotton, rice, tomato, wheat, corn, eggplant, etc.) and focuses on vision models (CNN, SVM, LSTM, ViT), reporting over 89% accuracy in disease detection tasks.

While their "Application" category centers on specific use cases such as symptom classification and segmentation, our perspective highlights productive systems (greenhouses and large-scale farms) where the convergence of sensors, LoRaWAN networks, and predictive algorithms creates greater added value. In this sense, the results of [80] validate the technical feasibility of AI techniques in various crops, while our analysis reveals the types of farming systems—particularly those with high density and environmental control—where these technologies find more intense and profitable adoption.

The high concentration of papers in greenhouses and high-value crops suggests that the adoption of Generative AI and IoT is more feasible in contexts with greater environmental control and economic return. This insight could be extrapolated to sectors such as logistics, pharmaceutical industries, or smart laboratories.

This trend also presents an opportunity to replicate such approaches in emerging agricultural regions through technology transfer policies. Furthermore, it highlights the need to expand research toward less-studied crops and open-field environments, promoting technological equity.

In the future, this distribution can serve as a model for prioritizing investments in other data-intensive and automation-driven industries.

RQ2: Which IoT devices are most frequently used in scientific studies on Precision Agriculture?

Table 3 and Figure 6 present the frequency of occurrence for each key platform or sensor in Precision Agriculture research, justifying their selection due to reliability, versatility, and ease of integration in real-world environments.

Raspberry Pi (~40%) and soil moisture sensors (~37%) clearly dominate the IoT landscape in Precision Agriculture, reflecting a preference for local computing platforms and critical water monitoring to optimize irrigation.

Multispectral drones (~16%) emerge as the third most frequent technology, highlighting the adoption of aerial captures with advanced spectral bands for crop health assessment. WSANs (~7%) underscore the need for distributed, resilient, and long-range networks.

Table 2. Crops identified in the reviewed papers

Crops	Papers	Count	%
Oil palm	[39]	1	0.9
Tomato	[11] [16] [22] [23] [31] [39] [44] [63] [69]	9	8.5
Grape	[5] [14] [19] [26] [29] [33] [36] [39] [45] [61] [69]	11	10.4
Rice	[10] [15] [16] [20] [21] [25] [28] [31] [35] [41] [43] [52] [53] [54] [58] [63] [64] [65] [66] [69]	20	18.9
Green-house (various vegetab-les)	[1] [2] [4] [5] [9] [10] [11] [14] [16] [17] [19] [22] [24] [27] [29] [31] [33] [34] [35] [36] [38] [39] [40] [41] [47] [48] [50] [52] [53] [54] [55] [58] [59] [61] [62] [63] [64] [67] [68] [69] [71] [73]	45	42.5
Vineyard	[2] [11] [19] [25] [26] [36] [38] [48] [61] [70]	10	9.4
Potato	[2] [4] [5] [22] [29] [58] [63] [69]	8	7.5
Onion	[36] [63]	2	1.9

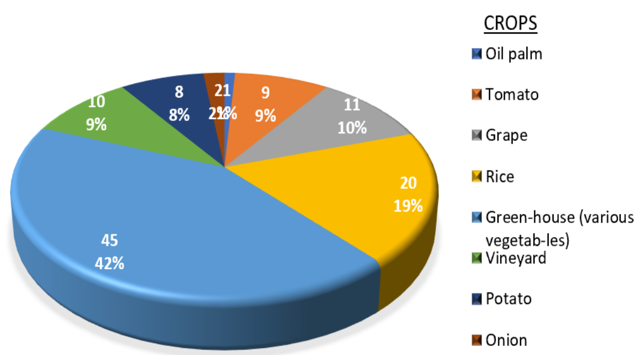

Fig. 5. Number of papers by crop

Table 3. IoT devices identified in the reviewed papers

IoT Devices	Papers	Count	%
Raspberry Pi	[1] [5] [14] [16] [19] [20] [26] [27] [31] [41] [42] [49] [53] [55] [67] [69] [71]	17	39.5
Multispectral drones (RGB + Red-Edge)	[23] [25] [35] [39] [61] [64] [69]	7	16.3
Soil moisture sensor	[1] [2] [4] [5] [11] [12] [13] [19] [24] [25] [32] [33] [35] [37] [52] [71] [73]	16	37.2
WSANs (Wireless Sensor & Actuator Nodes)	[1] [63] [67]	3	7.0

Our distribution of IoT devices in precision farming—where Raspberry Pi accounts for 39.5%, soil moisture sensors 37.2%, multispectral drones 16.3%, and WSANs 7.0%—is fully consistent with prior studies. Terence and Purushothaman [76] had already identified in 2020 that low-cost platforms (Raspberry Pi and Arduino-based MCUs) were the most widely used in smart farming. Similarly, Hoteit et al. [79], in their review of smart irrigation, confirmed the widespread adoption of microcontrollers such as Arduino UNO, ESP8266/32, and Raspberry Pi for data acquisition and transmission. Collectively, these device–sensor pairings emphasize a sustained evolution

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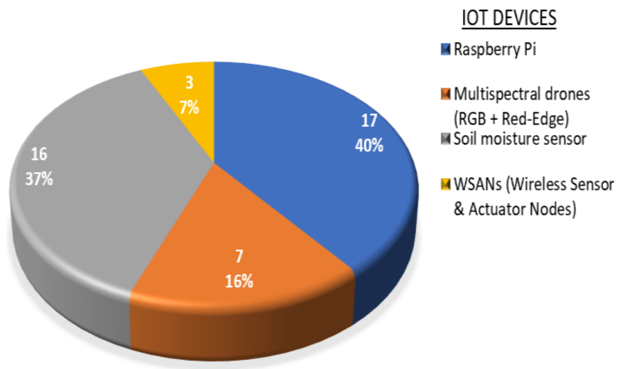

Fig. 6. Pie chart of papers by IoT device

Table 4. Main topics extracted from the abstracts

Topic Name for Summaries	Word 01	Word 02	Word 03	Word 04	Word 05	Word 06	Word 07	Word 08	Word 09	Word 10	Weight
1. Smart agriculture based on data and sensors	smart	datum	sensor	agricultu re	use	base	system	paper	model	precisión agricultu re	0.09
4. Technology and data usage in smart agriculture	datum	system	agricultu re	use	base	technolo gy	Smart farme	internet thing	applicati on	crop	0.09
3. Image modeling for smart agriculture	image	model	framewo rk	condition	crop	time	plant	provide	smart farming	quality	0.08
5. Precision agriculture and technology: use and performance	precisión agricultu re	use	technolo gy	performa nce	model	agricultu re	datum	network	applicati on	provide	0.08
2. Use of network models for precision agriculture	use	base	model	network	precision agricultu re	system	node	monitor	environ ment	agricultu ral	0.07

toward open, low-cost, low-power MCU-based architectures that facilitate the integration of Generative AI and IoT in Precision Agriculture.

The prevalence of open and low-cost platforms such as Raspberry Pi and soil moisture sensors highlights an accessible technological ecosystem that can be adapted to sectors like environmental monitoring, smart cities, or community health in rural areas. Their low cost and ease of deployment allow technological solutions to be scaled in regions with limited resources. Furthermore, the adoption of multispectral drones and WSANs anticipates their potential application in industries such as mining, water management, and environmental conservation. This trend reinforces the feasibility of modular and sustainable systems to address emerging challenges across various geographic and temporal contexts.

RQ3: What are the most frequently used concepts (topics) in abstracts of research on Generative AI and IoT in Precision Agriculture?

Table 4 illustrates the main topics identified in the abstracts of research related to Generative AI and IoT in Precision Agriculture. These topics are derived from a clustered keyword analysis, reflecting dominant semantic patterns in the most representative studies.

According to the table, the most frequent topics revolve around the use of sensors, drones, and neural networks to optimize smart agriculture. A strong focus on models, data, and performance is evident, emphasizing the importance of predictive analytics and automation. Terms such as monitoring, precision, environment, and

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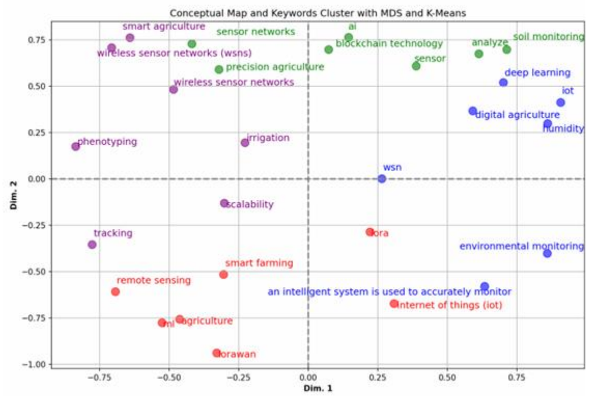

Fig. 7. Conceptual map of keywords

Table 5. Cluster name extracted from the keywords

Cluster Name	Weight	Avg. Dim. 1	Avg. Dim. 2
1. Smart agriculture and IoT monitoring	55	-0.26	-0.65
2. Precision agriculture and smart sensors	41	0.17	0.68
3. Internet of Things and artificial intelligence	43	0.69	0.09
4. Smart agriculture and sensor networks	21	-0.57	0.26

smart_farming highlight a clear orientation toward sustainable and technologically advanced farming practices. The use of vision-based technologies and networks for environmental monitoring also stands out. Collectively, these topics reflect an evolution toward more integrated, intelligent, and efficient agricultural systems.

When comparing our five extracted topics with the research areas analyzed in the fourteen systematic reviews by [84], we find that only our work simultaneously delves into image classification and its integration into IoT platforms for smart agriculture. In contrast, the previous reviews tend to focus on one aspect or the other. For example, in [84], all studies are marked "✓" for either image classification or IoT solutions, but none show "✓" in both columns. In contrast, our review integrates advanced visual data processing (deep learning, segmentation, pest and stress detection) with practical deployment on IoT platforms (LoRaWAN, MQTT, Raspberry Pi). This shows that our contribution bridges a significant methodological gap by unifying image classification and IoT implementation in Precision Agriculture.

The simultaneous integration of computer vision and IoT platforms in agriculture demonstrates an advanced methodological approach that can be replicated in sectors such as automated manufacturing, environmental management, and public health to improve monitoring and decision-making. This unified model promotes intelligent systems adaptable to diverse geographical contexts, especially in regions with critical efficiency needs. The orientation toward predictive analysis and sustainability reinforces its future applicability in scenarios involving climate change and resource scarcity. Moreover, the identified methodological gap opens opportunities for interdisciplinary research in other data-driven industries.

RQ4: What conceptual clusters can be identified from the analysis of the most frequent keywords in studies on Generative AI and IoT applied to Precision Agriculture?

Figure 7 and Table 5 present a conceptual map with clusters formed from keywords in research on Generative AI and IoT applied to Precision Agriculture, providing a visual understanding of the conceptual evolution in this field.

The grouped concepts reveal a clear thematic differentiation, ranging from advanced technologies to specific IoT applications in digital agriculture. The frequent use of terms such as sensor networks and blockchain technology reflects an evolution toward increasingly integrated and secure intelligent systems. The largest cluster corresponds to "Advanced technologies for smart agriculture," underscoring the current emphasis on sophisticated technological solutions. Additionally, a direct connection between deep learning and the precise management of agricultural variables is observed, highlighting growing technological specialization. Finally, concepts such as remote sensing and tracking point to the continued interest in remote and precise crop monitoring.

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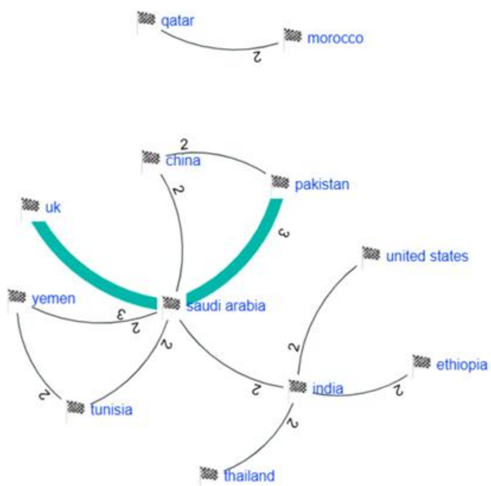

Country1	Country2	Weight
pakistan	saudi arabia	3
saudi arabia	uk	3
china	pakistan	2
china	saudi arabia	2
ethiopia	india	2
india	saudi arabia	2
india	thailand	2
india	united states	2
morocco	qatar	2
saudi arabia	tunisia	2
saudi arabia	yemen	2
tunisia	yemen	2
Total		**26**

Fig. 8. Bibliometric collaborations between countries

These findings not only corroborate the topics identified in [82] but also extend the taxonomy of smart environments described by González-Palmié et al. [78]. Our red cluster, “Advanced technologies for smart agriculture” (weight 55), matches the Motor Themes in [82] such as “Smart Agriculture” and “Artificial Intelligence,” while also encompassing the perception and networking dimensions from [78] by emphasizing terms like IoT, LoRaWAN, and sensor networks. Similarly, the green cluster, “Precision agriculture and advanced sensors” (weight 41), mirrors the Motor Themes “Precision Agriculture” and “Sensor” in [82] and represents the transition, noted in [78], from isolated nodes to high-performance heterogeneous networks. Our third cluster, “IoT applications in digital agriculture” (weight 43), appears in [82] as an emerging Niche Theme and aligns with the intelligent processing dimension in [78], where deep learning and blockchain technology become increasingly relevant. Lastly, the purple cluster, encompassing remote sensing and tracking (weight 21), corresponds to the Emerging Themes in [82] and the application dimension in [78], underscoring the current priority on remote monitoring and the generation of value-added services. Thus, our conceptual evolution not only validates both classifications but also reveals increasing specialization in Generative AI and IoT for Precision Agriculture.

The conceptual evolution toward advanced technologies such as sensor networks, blockchain, and deep learning suggests a replicable trajectory in sectors like logistics, food traceability, and smart healthcare, where security, automation, and remote monitoring are priorities. This specialization reinforces the ability of these technologies to adapt to diverse geographic contexts, including rural or hard-to-reach areas. Moreover, the emergence of thematic clusters helps anticipate future lines of interdisciplinary technological innovation. In the long term, this evolution may guide the digital transformation of emerging industries through more robust and secure intelligent architectures.

RQ5: Which countries frequently exhibit co-occurrence in research on Generative AI and IoT in Precision Agriculture?

Figure 8 presents a bibliometric network visualizing international collaboration among countries, clearly highlighting those with the most frequent co-occurrence in research on Generative AI and IoT in Precision Agriculture.

A strong international collaboration is evident, led by Saudi Arabia and India, underscoring their role as central countries in research on Generative AI and IoT in Precision Agriculture. Saudi Arabia’s repeated cooperation with Pakistan, the United Kingdom, China, India, and Yemen reflects a consistent and strategic pattern of scientific and technological knowledge exchange within the Asian and Middle Eastern regions. Additionally, recurrent interactions between Thailand and India, Tunisia and Yemen, and India with Ethiopia, as well as Qatar with Morocco, indicate emerging regional networks that foster geographic diversification of knowledge and technology transfer.

When comparing our country-based distribution of papers with that of Restrepo-Arias et al. [84], clear parallels emerge: in both studies, India stands out with overwhelming leadership (31 papers in our review versus the highest number reported in [84]), confirming its position as the main source of scientific output in Generative AI and IoT for Precision Agriculture. These co-occurrence patterns also closely match the geographic affiliations reported by Abdelmoneim et al. [79], who identified Pakistan and Saudi Arabia as key contributors (9 and 7 authors, respectively), which aligns with our weight-3 link between both countries. Likewise, Abdelmoneim et al. highlight China and India in prominent positions (6 and 5 authors), consistent with our weight-2 links between China–Saudi Arabia and India–Ethiopia and Thailand.

Finally, de Avila and Barbosa [77] show that, among 277 authors in 71 studies on smart agricultural environments, India accounts for the highest proportion of affiliations (107 authors, 38.6%), while Saudi Arabia is represented by 7 authors (2.5%), reinforcing our observation that both countries act as central nodes in the co-occurrence network. Overall, the paper and author counts by country in [84], [79], and [77], as well as the mapped link structure in our co-occurrence figure, consistently highlight India and Saudi Arabia's prominence as hubs of international collaboration in Generative AI and IoT research applied to Precision Agriculture.

The centrality of India and Saudi Arabia in scientific co-occurrence networks reflects their ability to lead global technological initiatives, serving as a replicable model for sectors such as energy, healthcare, and digital education through South-South alliances. These collaborations strengthen knowledge transfer to developing regions, fostering more inclusive innovation ecosystems. Furthermore, the observed geographic diversification suggests a shift toward more distributed science, moving away from traditional power concentrations. In the future, these international networks may serve as foundations for multilateral technological innovation programs tailored to both global and local challenges.

5 Conclusions and Future Research

This paper examined the integration of Generative AI and IoT in Precision Agriculture, addressing key questions regarding crops, devices, concepts, and scientific collaborations. Regarding RQ1, a high concentration of studies was found on greenhouses, rice fields, vineyards, tomatoes, and potatoes, indicating a stronger adoption in high-value crops and environments with controlled conditions. RQ2 revealed that devices such as Raspberry Pi and soil moisture sensors dominate the technological landscape, alongside multispectral drones and wireless networks, shaping an efficient and low-cost architecture. In RQ4, thematic clusters showed a clear evolution toward integrated intelligent systems, emphasizing concepts such as sensor networks, deep learning, blockchain, and remote monitoring. Finally, RQ5 evidenced a strong international collaboration network, with India and Saudi Arabia as central nodes and emerging alliances in Asia and Africa. Collectively, the findings confirm that these technologies are in a stage of consolidation, with high potential for adaptation, replicability, and expansion across different global regions.

The implications of this systematic review open several avenues for future research. First, it is relevant to explore how Generative AI and IoT-based solutions can be adapted to low-commercial-value crops or regions with limited resources, assessing their operational sustainability. Second, the development of integrated platforms that combine computer vision, edge computing, and generative models for real-time decision-making is recommended. Third, the evolution of concepts such as blockchain and sensor networks should be studied in terms of their applicability to agricultural traceability and data governance. Fourth, fostering collaborative networks in underrepresented regions such as Latin America and Africa is advised to reduce technological gaps and strengthen research equity. Finally, future studies may focus on the technological transfer of these architectures to sectors such as digital health, advanced manufacturing, or environmental management, promoting their adoption beyond the agricultural domain.

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