

Review

Artificial Intelligence, Foundation Models, and Digital Twins for Climate-Resilient Agriculture: A Review

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Abstract: Climate change, increasing food demand, and resource constraints are accelerating the transition from conventional precision agriculture toward smart, autonomous, and climate-resilient agricultural systems. Artificial intelligence (AI), foundation models, digital twins (DTs), the Internet of Things (IoT), remote sensing, edge-cloud computing, and big data analytics are emerging as key technologies for data-driven agricultural management. This review critically evaluates recent advances in AI-driven intelligent agriculture, with emphasis on machine learning, deep learning, explainable AI (XAI), generative and agentic AI, multimodal foundation models, and digital twins, together with the sensing and computing infrastructures required for their deployment. Relevant literature was identified using keywords related to AI, foundation models, digital twins, IoT, precision agriculture, and climate-resilient agriculture, with emphasis on recent peer-reviewed studies addressing technological applications, performance, limitations, challenges, and future prospects. The selected literature was critically synthesized to identify technological trends, knowledge gaps, and emerging research opportunities. The review highlights that the greatest potential of intelligent agriculture lies in integrating heterogeneous data from sensors, UAVs (unmanned aerial vehicles), satellites, weather systems, field operations, and agricultural knowledge to support context-aware prediction, decision-making, and autonomous action. However, data quality, model generalizability, explainability, interoperability, cybersecurity, computational requirements, and large-scale field validation remain major challenges. This review further develops an integrated perspective connecting AI, foundation models, multimodal data infrastructures, digital twins, and autonomous agricultural systems within a unified cyber-physical ecosystem. Future priorities include trustworthy AI, agentic decision-making, semantic interoperability, federated learning, continuous learning, and self-learning digital twins toward Agriculture 6.0.

Keywords: Artificial Intelligence; Foundation Models; Digital Twins; Climate-Resilient Agriculture; Precision Agriculture; Smart Farming

1. Introduction

Agriculture is going through a significant revolution as the world struggles to ensure food security while addressing the negative effects of climate change. According to forecasts, the global population will be around 9.7 billion people in 2050, and the demand for food, water, and other agricultural necessities will be significantly higher. At the same time, higher temperatures, unpredictable rainfall, droughts, floods, soil depletion, loss of biodiversity, and pest infestations are posing serious challenges to agriculture [1]. Traditional approaches to farming that are highly reliant on traditional observation, past experience, and response management are proving insufficient in

tackling these changing environmental conditions. It is necessary to design agricultural systems that are resilient to climate change and are able to improve production while reducing negative effects on the environment and making efficient use of natural resources. New developments in precision agriculture, smart agriculture, and digital agriculture have shown significant promise in tackling these issues through the use of sensing and analytics [2].

The fast pace of development of Artificial Intelligence (AI) has shifted from traditional agriculture towards intelligent and automated agriculture more quickly. The use of Machine Learning (ML), Deep Learning (DL), computer vision, IoT, remote sensing, GIS, GPS, unmanned aerial vehicles (UAVs), cloud computing, and robotics makes it possible to continuously monitor crops, soil, weather conditions, livestock, and agricultural equipment. All these technologies analyze large amounts of diverse data for the purposes of predicting crop yield, diagnosing diseases, detecting weeds, planning irrigation, optimizing fertilization, precise spraying, and harvesting crops autonomously [1]. There is evidence from recent systematic reviews that AI techniques, especially CNNs (convolutional neural networks), ViTs (vision transformers), and hybrid learning algorithms, have advanced the process of detecting plant diseases and implementing precision agriculture through increased accuracy and efficiency without increasing production costs or adverse environmental effects. In a similar way, the use of AI-driven unmanned vehicles with computer vision and intelligent navigation technology has increased efficiency and automation on farms, which is a move towards Agriculture 4.0 [3].

In recent years, the advent of foundation models (FM) represents another innovation in the field of artificial intelligence for agriculture. In contrast to traditional AI models which are built for single purposes and the foundation models are trained on large multimodal datasets and can easily be used for various purposes in the agricultural sector with fine-tuning, prompting, and retrieval-based generation. The capability of agricultural foundation models like language, vision, and multimodal models has been shown to be outstanding in crop classification, pest and disease detection, image segmentation, agricultural knowledge question answering, smart advisory systems, and agricultural robots [4]. Recent studies have shown that there is an additional possibility for foundation models to become intelligent engines of reasoning, which will help with improving the decision-making process and making it better for agriculture, and allowing for fusion of data from multiple sources. In addition, it was shown that the foundation models will be able to significantly decrease the amount of effort required for developing the Digital Twins, as they will be able to create their simulation models and predictions on their own [5]. Collectively, these studies indicate that the major contribution of AI and foundation models in agriculture is not limited to improving individual prediction or classification tasks. Their greater potential lies in integrating heterogeneous information from images, sensor observations, weather records, field operations, and textual agricultural knowledge to support context-aware decision-making. However, the current evidence remains largely application-specific, with relatively limited validation of foundation-model-based systems under diverse agro-climatic and farm-scale conditions. This indicates a need to move from task-oriented AI applications towards integrated and continuously learning agricultural intelligence.

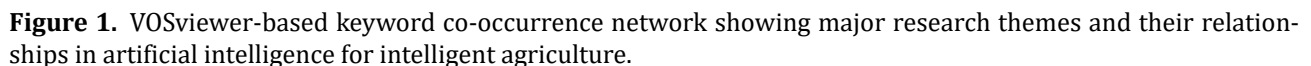
Recent reviews suggest that Digital Twin (DT) technology is a promising approach for the development of intelligent agriculture. In general, a Digital Twin is an interactive and dynamic model of a physical agricultural system that constantly exchanges information with a corresponding physical system using IoT devices, sensors, remote sensing systems, artificial intelligence models, cloud computing, and predictive models. Unlike digital models, DT enables two-way communication between the physical world and the virtual world [6]. In recent years, reviews have shown that Digital Twins have successfully been used for crop growth monitoring, greenhouse management, irrigation scheduling, livestock production, machinery improvement, precision agriculture, and climate change adaptation. Nonetheless, existing solutions lack cohesion and concentrate only on specific agricultural assets without considering their integration into an ecosystem at the farm scale. Additionally, issues associated with interoperability, semantics, heterogeneous data integration, architectures, scalability, cybersecurity, and large-scale validation are still constraining the application of Digital Twins in agriculture [7]. A structured literature search was conducted using relevant scientific databases to identify recent studies on AI, foundation models, digital twins, IoT, remote sensing, and climate-resilient agriculture. The literature was screened based on relevance to the scope of the review, publication period, and availability of sufficient scientific information, followed by critical synthesis of the selected studies.

To our knowledge, this review provides one of the first comprehensive overviews integrating Artificial Intelligence, Foundation Models, and Digital Twins in the context of climate-resilient intelligent agriculture. Different from previous works where these technologies have been discussed individually, the key innovations of this review are threefold: (i) integration of AI, foundation models, digital twins, and intelligent data infrastructures within a

This network visualization illustrates the interconnected research trends in agriculture. The central hub consists of large, dark blue nodes for 'artificial intelligence' and 'machine learning'. Radiating from this center are several major clusters:

- Decision Support Systems:** A large green cluster on the left includes terms like 'decision support systems', 'decision trees', 'water management', and 'nutrients agricultural management'.
- Computer Vision & Deep Learning:** A large blue cluster on the right includes 'computer vision', 'deep learning', 'object detection', 'deep neural networks', and 'plant disease classification'.
- Internet of Things & Smart Farming:** A red cluster at the bottom left includes 'internet of things', 'smart farming', 'cloud computing', and 'cyber attacks'.
- Other Key Areas:** Smaller clusters include 'crop yield', 'disease diagnosis', 'genetic algorithm', 'data mining', 'unmanned aerial vehicles (uav)', and 'robotics'.

 The size of each node represents its relative frequency or importance in the research landscape, while the lines (edges) connect related concepts, showing a highly integrated and interdisciplinary field.



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and sufficiently developed evidence. These recent studies were considered as emerging evidence and were interpreted cautiously, particularly for technologies that are still undergoing validation and large-scale deployment. The inclusion of recent literature is intended to capture the current direction of the field rather than imply that these emerging approaches have reached a settled consensus.

2. Artificial Intelligence and Foundation Models

2.1. AI Techniques for Agriculture

In contemporary agriculture, artificial intelligence (AI) technology has become a breakthrough for an automated analysis of big data coming from various heterogeneous sources within field environments. As seen in **Figure 2**, the process of applying AI starts with the acquisition of multi-source data through UAVs, RGB cameras, hyperspectral imaging (HSI), thermal imaging (TRI), and IoT-based sensors. All these devices continuously collect information about crop physiology, soil properties, microclimate, and environmental variations with high spatiotemporal resolution. This ensures complete data sets for remote sensing and sensor networks, which enables precision farming and real-time decision-making [8].

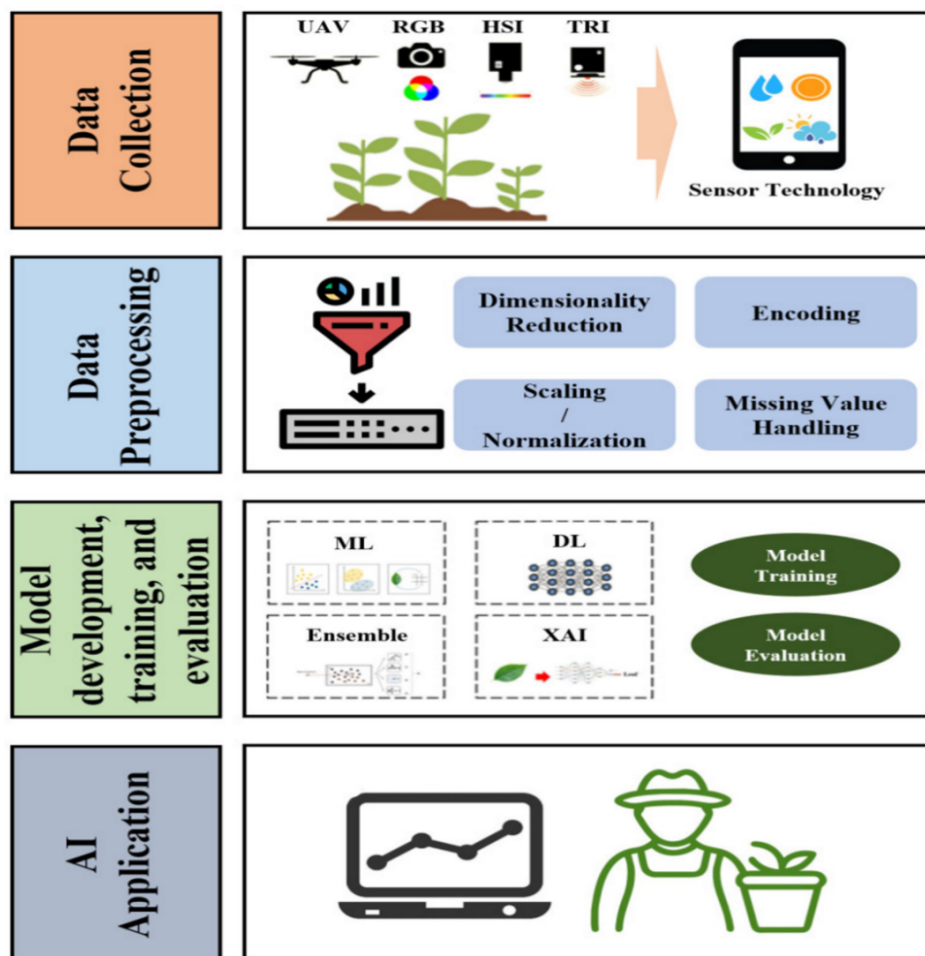


Figure 2. General workflow of AI-based intelligent agriculture from data acquisition to practical applications.

Note: Reproduced from Choi et al. [8] under the copyright license CC-4.0.

These datasets are pre-processed in a rigorous manner to boost data quality and efficiency of computation prior to developing models. The methods of preprocessing, which include dimensionality reduction, feature encoding, normalization, scaling, and filling missing values, reduce redundancy and noise while improving feature representation [9]. After preprocessing, sophisticated AI techniques, including machine learning (ML), deep learn-

ing (DL), ensemble learning, and explainable artificial intelligence (XAI), are applied for predictive modeling and pattern recognition purposes. Machine learning is extensively applied to classify, regress, and cluster, while deep learning structures automatically learn hierarchical features from high-dimensional data sets such as images and sensors, resulting in better performance in complicated applications like disease diagnosis, crop phenotyping, and yield estimation. On the other hand, ensemble learning techniques increase the robustness of the models by using several predictive models [10].

AI model output is used to implement these technologies in agriculture through precision irrigation scheduling, nutrition management, weed detection, crop health assessment, yield estimation, and resource utilization. The above-mentioned AI-based decision support systems enable site-specific farm management which increases productivity, saves water, reduces fertilizer usage, minimizes pesticide spraying, and decreases GHG emission [11]. Recent studies suggest that AI can serve as an important computational component of intelligent agriculture, supporting the development of technologies such as foundation models, multimodal learning, and digital twins for prediction and adaptive decision-making under changing climatic conditions.

2.2. Foundation Models and Multimodal AI

Recent studies have described foundation models as a class of artificial intelligence that can learn general-purpose representations through pre-training on large datasets and can potentially be adapted to various agricultural applications through task-specific tuning. As shown in **Figure 3**, the development of foundation models goes from Large Language Models (LLMs) which process text data to Large Vision Models (LVMs) which deal with visual data to finally reach Multimodal Large Language Models (MLLMs) which use data from different data sources [12]. Unlike traditional artificial intelligence frameworks that have been designed to serve a particular application only. The foundational models offer a generalized framework that can effectively understand the complex relations between text-based descriptions, field visuals, sensors, satellite images, and environmental factors [13].

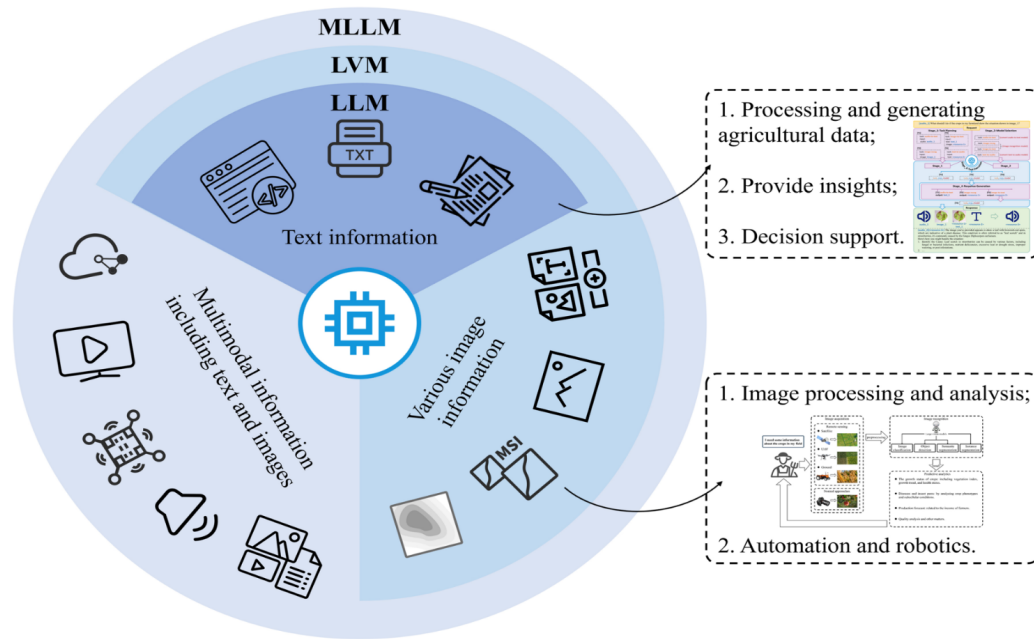


Figure 3. Evolution of LLMs, LVMs, and MLLMs for multimodal agricultural data processing, image analysis, and intelligent decision support.

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Moreover, the above figure illustrates multimodal AI integrates a variety of information from agriculture, such as text, RGB imagery, MSI and hyperspectral images, video streams, sensor data, and cloud-based databases, into one representation space. Multimodal AI allows for an analysis of both semantic and visual information at once, which makes it possible to understand crop growth, diseases, nutrition deficits, soil conditions, and stress of plants

better. Due to the use of transformer architecture and cross-modal attention mechanisms, multimodal AI models can integrate heterogeneous datasets much more efficiently than classic machine learning and deep learning models that use only one type of data [14].

The combined capabilities of foundation models and multimodal AI can be applied to many different applications within agriculture, such as automatic agricultural data production, knowledge mining, image analysis, crop monitoring, disease detection, automation, and decision-making support. Zero-shot and few-shot learning makes their adaptation to novel crops, new geographies, and climate conditions possible with minimal amounts of labeled data, which is one of the significant problems of conventional AI [15]. This implies that foundation models are an evolution step from agricultural intelligence to enable the computational infrastructure of digital twins, sensing technologies, and climate-based decision-making systems, which will ensure sustainable agricultural systems through automation and resilience [16].

2.3. Explainable, Generative, and Agentic AI in Agriculture

The fast-paced development of AI technology has resulted in the formation of new approaches to AI like explainable, generative and agentic AI, which go beyond traditional analytics towards autonomous decision-making in agriculture. As seen in **Figure 4** below, the process starts with collecting information on a multi-layer data basis, including information obtained from drones, sensors, satellite imagery, weather stations, videos and imaging systems [17]. Multimodal datasets are used for integration at the level of perception and processing to derive a holistic understanding of agricultural environment through data fusion, cleansing, transformation, and knowledge representation. Recent breakthroughs in the realm of generative AI and multimodal foundation models have made a tremendous contribution to this step by adding missing data, deriving recommendations in context, and distilling semantic knowledge from multimodal data inputs [18].



Figure 4. AI-driven multimodal framework for intelligent agricultural data processing, decision-making, and adaptive farm management.

Note: Reproduced from Davcev et al. [17] under the copyright license CC-4.0.

The information that has been analyzed will be sent to the decision-making stage, where different independent AI agents will work together to analyze the environment, coordinate agricultural processes, and make decisions to manage the processes better. While conventional machine learning algorithms perform tasks pre-assigned to them, agentic AI uses planning and reasoning for making decisions independently [19].

On the other hand, XAI solutions help maintain transparency and explainability of these self-decisions by attributing features, attention mechanisms, and understandable explanations. This explains such interpretability fosters user trust and helps achieve regulatory compliance and validation of recommendations provided by the system [20].

These decisions generated are implemented using the action layer whereby reinforcement learning constantly refines operational policies depending on the environment feedback and performance measures. The feedback and learning layers facilitate continual model improvement by way of error correction, adaptive learning, and performance measures, enabling agricultural systems to become better in subsequent growing seasons [21]. During the process, the entire ethical and governance framework plays a role in ensuring privacy preservation, fairness evaluation, transparency, and cybersecurity. All these elements combined create an intelligent and autonomous agricultural system through the emergence of explainable, generative, and agentic AI that makes it possible for the agricultural sector to be sustainable and adaptable to the changing environment [22].

3. Digital Twins for Climate-Resilient Agriculture

3.1. Digital Twin Architecture and Workflow

The concept of digital twin creates a dynamic cyber-physical environment wherein the real agricultural system is kept synchronized constantly with its digital twin to facilitate intelligent monitoring, simulation, and decision making. In the architecture of digital twins, there is the physical farm which involves the continuous acquisition of heterogeneous data from IoT-based sensor devices, CCTV cameras, weather stations, soil and nutrient sensors, irrigation systems, and climate control systems. These sensors gather the real-time data regarding environmental condition, crop development, equipment condition, and farm activities whereas the external weather stations and renewable energy system provide additional climatic and operational data respectively [23].

The collected information is sent to the edge computing layer known as Farm Manager where middleware, intelligent controllers, and physical to virtual communication module handle and manage the data before its synchronization with the virtual world. The intermediate layer facilitates the management of sensors and actuators, maintains environmental control, and provides real-time visualization and device management [24]. The processed information is integrated into the virtual farm, where digital models, simulators, visualization, and rule-based systems simulate the behavior of the physical agricultural system on a constant basis. It is the two-way communication that the virtual model updates itself while sending the best possible operating strategy to the physical farm at the same time [25].

Furthermore, the Digital Twin Platform has advanced integration of artificial intelligence, big data analytics, and continuous learning capabilities for prediction farm management and self-driving decisions. Artificial Intelligence is used to analyze the data sets to spot any anomalies, automate irrigation scheduling, control the environment, and predict the system performance in the future [26]. Additionally, the use of visualization interface systems, dynamic simulation systems, and virtual farm management systems enables people to test various management plans before their implementation, hence reducing risks and improving the accuracy of decisions. In essence, digital twins have led to the evolution of traditional farming methods into a smart and closed looped cyber physical system that is capable of continuous monitoring, predictive simulations, operation optimization, and climate resilient agriculture [27].

3.2. Integration with AI and IoT

The integration of AI and IoT with digital twins provides the intelligence and connectivity required for continuous synchronization between the physical farming environment and its virtual replica. The following **Figure 5** shows that heterogeneous agricultural data is constantly collected using IoT technologies like soil moisture sensors, environmental sensors, weather stations, drones, and satellite systems placed in agricultural fields [28]. These sensing devices represent the edge level, where data can be collected in real time and processed on-site to avoid

network delays and consume less bandwidth. Information that has been processed and travels across mobile and stationary fog levels to enable intermediate computation, resource scheduling, field planning, coordination of multiple autonomous devices, and eventually delivery of important information to cloud-based digital twin services. Such a cloud-fog-edge structure greatly enhances scalability and real-time performance needed for precision agriculture [29].

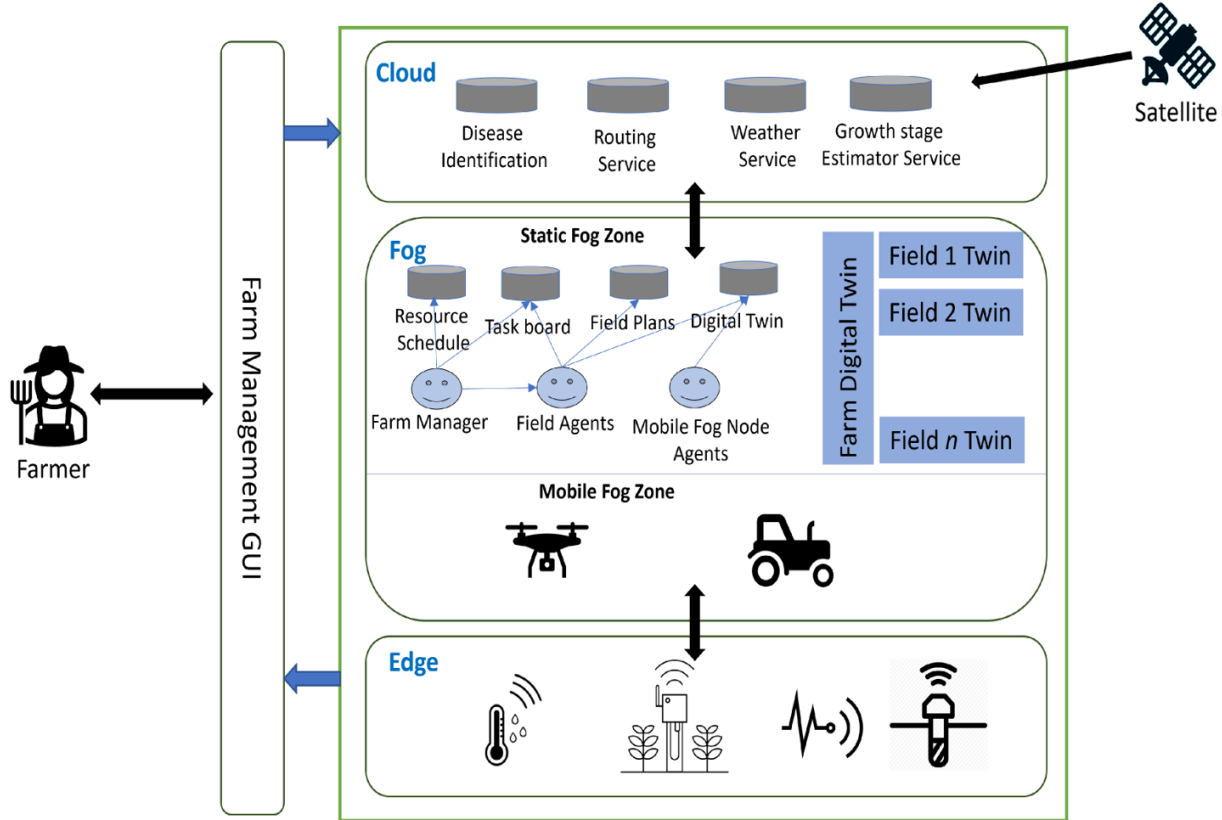


Figure 5. Cloud-fog-edge architecture with digital twins for intelligent and autonomous farm management.

In terms of providing intelligence on the farm through AI, the cloud layer provides the platform whereby the AI-based analytical services can be combined with digital twins for comprehensive management of farms. The cloud services provide services for diseases detection, weather prediction, routes optimization, and growth stage predictions through the integration of historical databases with data from the field in real-time. The farm digital twin, on the other hand, is able to replicate the physical condition of various agricultural fields virtually [30]. The continuous analysis of multisource data coming from the edge devices and digital twins is performed in order to optimally schedule irrigation, fertilizer applications, pest scouting, and machinery operations. This two-way communication channel between real-world farms and their digital twins provides the creation of the closed-loop monitoring system where the virtual models are updated based on the changing environment and crops conditions [31].

The smooth interaction between all these technologies facilitates decision support systems that have capabilities to manage the farms autonomously in a way of climate resilient. Through continuous observation, analysis, and feedback, the combined framework allows for early detection of diseases, resource management, crop management, and field management [32]. In addition, the hierarchy-based structure also facilitates interoperability of different types of sensors and helps in scalable deployment in various agricultural farms. As a result, AI and IoT based digital twin technology is a crucial paradigm for next generation climate smart agriculture as it can be used to implement adaptive and data-driven management approaches for agriculture [32].

3.3. Applications in Crop, Soil, Livestock, and Greenhouse Systems

The application of digital twin technology together with artificial intelligence (AI) and Internet of Things (IoT) in agriculture has widened the range of its applicability to many agricultural systems where real-time monitoring and autonomous decisions can be made. The application of digital twin technology to crops is used for constant monitoring of crop growth, disease development, irrigation schedules, and crop prediction using the combination of different sources of data such as satellites, drones, on-field sensors, and weather stations. Digital twins in soils make use of soil physicochemical parameters, soil moisture changes, nutrients, and microorganism activities to optimize the processes of fertilization, irrigation, and carbon sequestration to improve the quality of the soil [28]. In animal husbandry, digital twin technology makes it possible to monitor animals' behavior and health parameters, feeding, diseases, reproduction, and welfare. Digital twins of greenhouses within the field of controlled environment agriculture consist of climate sensors, environmental control systems, and AI-based prediction models that help manage the temperature, humidity, CO₂ levels, lighting, and irrigation, which enables maximum resource-use efficiency and productivity. The table below provides an overview of the main applications of digital twins enhanced with AI technology in agriculture for crops, soil, livestock, and greenhouses. As shown in **Table 1** below, all these areas of agriculture employ various sensing technologies and predictions, together they provide smart management of resources [30].

Table 1. Applications of AI-enabled digital twin systems in agriculture.

Agricultural Domain	Data Sources	AI Techniques	Digital Twin Applications	Benefits	Challenges	Technological Maturity	References
Crop Systems	UAVs, satellites, IoT sensors, weather data	ML, DL, Computer Vision	Crop monitoring, disease detection, irrigation, yield prediction	Higher yield, resource efficiency	Data heterogeneity, scalability	Pilot Scale (emerging commercial applications)	Melesse [33]
Soil Systems	Soil sensors, weather data	ML, XAI, Time-series models	Soil health, nutrient management, moisture prediction	Improved fertility, water conservation	Sensor calibration, data scarcity	Pilot Scale	Vullaganti et al. [34]
Livestock Systems	Wearables, RFID, cameras	DL, Computer Vision, RL	Health monitoring, behaviour analysis, precision feeding	Better welfare, higher productivity	High monitoring cost, data privacy	Pilot Scale (some commercial solution)	Nawaz et al. [35]
Greenhouse Systems	Climate sensors, IoT devices	Predictive AI, RL	Climate control, irrigation, pest monitoring	Energy efficiency, improved quality	High infrastructure cost	Commercial Scale (limited to advance facilities)	Slimani et al. [36]
Smart Farm Systems	IoT, drones, satellites, cloud data	Foundation Models, Multimodal AI, Agentic AI	Farm simulation, decision support,	Climate resilience, sustainable farming	Interoperability, cybersecurity	Pilot to Commercial Scale (Rapidly advancing)	Tariq et al. [37]

4. Intelligent Data Infrastructure

4.1. IoT, Sensors, and Wireless Networks

The Internet of Things (IoT), sensor technology, and wireless networks primarily support data acquisition and communication in smart agriculture through continuous monitoring of field conditions and information exchange. As shown in **Figure 6**, the agricultural field is filled with various IoT-enabled sensors that constantly monitor important environmental and crop parameters, such as soil moisture, temperature, humidity, nutrient levels, and growing conditions of crops [38]. These sensors create huge amounts of real-time data that are first analyzed by edge computing systems nearby the location. Edge Computing systems analyze the incoming data, extract important features, and conduct local analysis, saving time, avoiding communication delays, and allowing for quick reactions to critical agriculture-related events like irrigation and detection of stressed crops. The analyzed data are further transferred to the cloud infrastructures using wireless communication methods like WiFi, LoRa, and 5G [39].

The cloud computing layer acts as the primary source of large-scale storage of agricultural data, deployment of machine learning models, and cloud analytics. Cloud computing systems process the heterogeneous data obtained from IoT sensors, satellite monitoring systems, and edge computing systems for the purposes of identification of diseases, crop health analysis, prediction and optimization. The machine learning system constantly processes the obtained data streams and makes intelligent decisions, whereas the updated prediction models are sent back to the

edge computing system for immediate execution. The communication between edge and cloud computing leads to a dynamic learning process wherein the AI models are continuously improved using new field data [40].

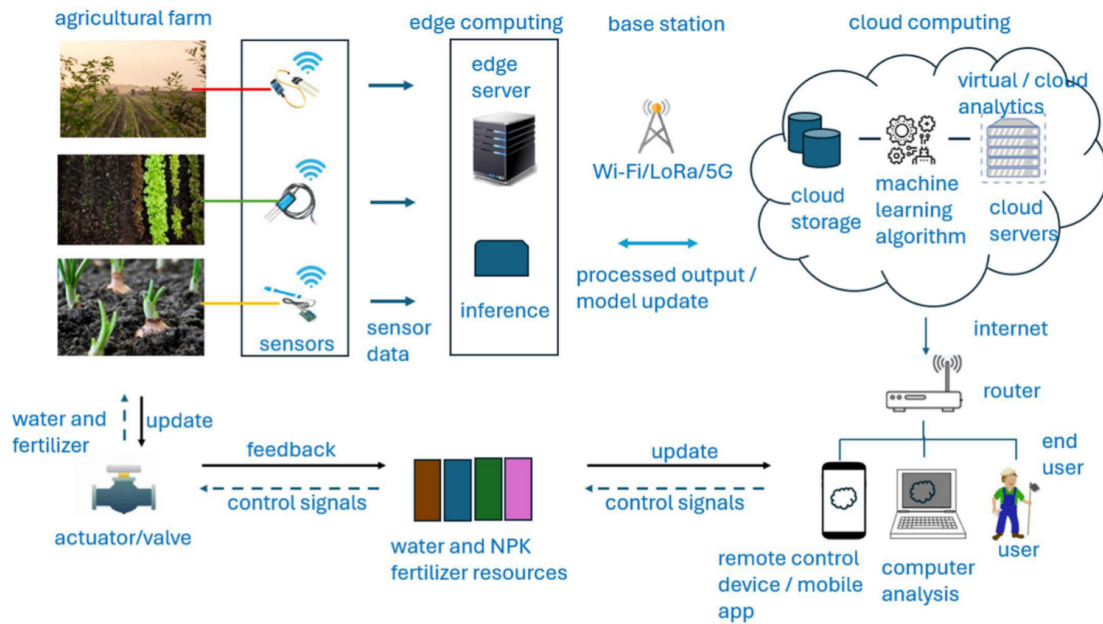


Figure 6. Edge–cloud computing framework for real-time smart irrigation and precision agriculture.

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Further, the use of the wireless network in association with the IoT sensing devices facilitates autonomous farm management through closed-loop feedback control via real-time monitoring. This is achieved by transmitting the smart signals of control produced via cloud computing to the mobile apps, farm management system, and automated actuator that controls irrigation valves and fertilizer distribution [41]. Field conditions can be monitored by farmers remotely using smartphones or computer dashboards to get analytical results and take appropriate decisions. The interconnected infrastructure greatly improves the efficiency of resource utilization, lowers manpower requirements, reduces wastage of water and fertilizers, and facilitates precision farming even in changing environmental conditions. Therefore, sensor networks connected through IoT, along with edge-cloud computing and wireless communications, become the key data infrastructure for intelligent and climate-resilient agriculture [42].

4.2. UAVs, Remote Sensing, and Satellite Technologies

UAVs, remote sensing, and satellite technologies have become crucial components for smart agriculture monitoring because of their capacity to perform fast, non-destructive and high-resolution analysis of crops. As shown in **Figure 7** below, the use of UAVs fitted with high resolution imaging sensors allows the collection of data in different regions of the electromagnetic spectrum such as visible, near-infrared, and thermal infrared [43]. Depending upon the application in agriculture, UAVs can be equipped with RGB sensors for visual imaging, multispectral cameras for assessing vegetation and nutrients, hyperspectral cameras for biochemical sensing, and thermal IR sensors for measuring canopy temperature and water stress. The capability to capture spectral data at different wavelengths allows detection of any physiological changes that cannot be observed by the naked eye [44].

The remote sensing techniques enable continuous assessment of crop status at various growth stages through the combination of observations from both air and ground. The UAVs carry out regular surveys of the crop farms in the whole growth cycle of the maize, resulting in the production of data concerning the physical state of the crop [45]. RGB imagery is frequently used for counting and characterizing plants, while multispectral and hyperspectral sensors measure vegetation indices, nutrient deficiencies, plant diseases, and stresses by means of spectral reflectance. Additionally, thermal infrared imaging can detect temperature differences within a canopy that occur due to drought, irrigation needs, and development of disease. The combination of all these sensing methods greatly increases the accuracy of crop monitoring in comparison with the traditional method of field observation [46].

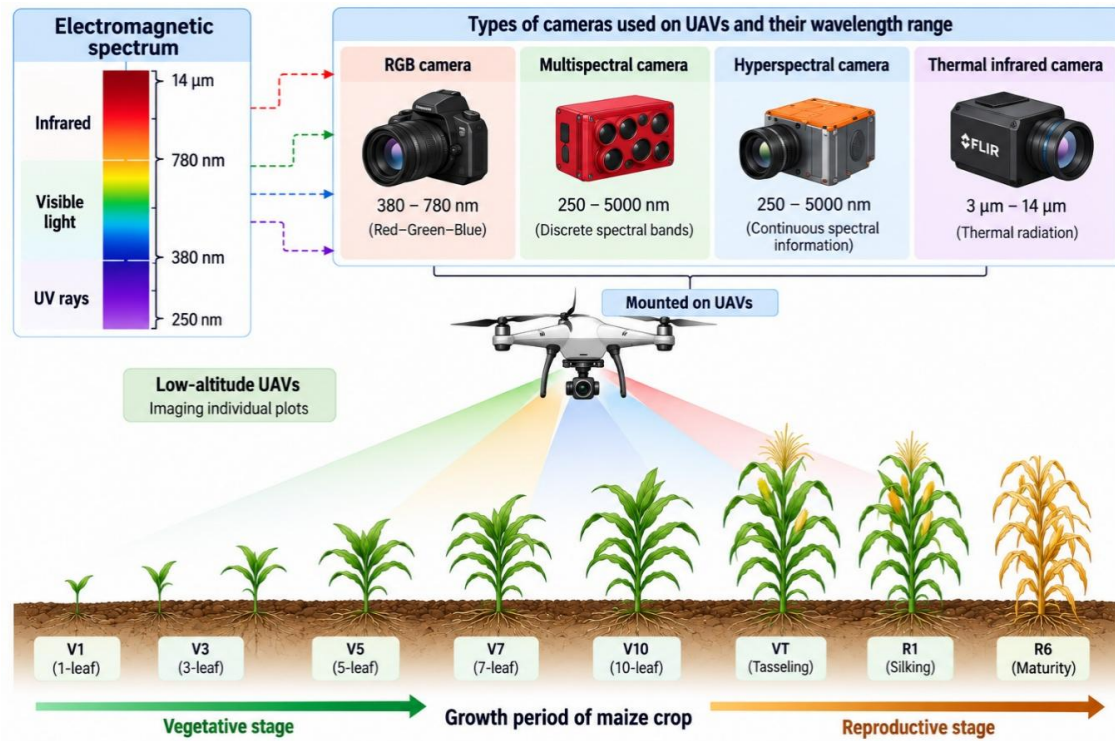


Figure 7. UAV-mounted multispectral imaging systems for monitoring maize growth across developmental stages.

The information collected through UAV platforms is increasingly combined with satellite observations and AI-based algorithms for the creation of a holistic system of agricultural monitoring that can enable precise farming at various levels of scale. Satellite imaging provides consistent large-scale monitoring for the assessment of crops in a region, whereas UAVs provide ultra-high-resolution information at the field level for validation purposes. AI models are used to process these multi-source data to carry out crop classification, detection of diseases, yield prediction, irrigation scheduling, and optimization of resources. Thus, the combination of UAVs, remote sensing, and satellites makes it possible to continuously monitor agriculture in a scalable manner with data, which becomes a key part of the intelligent data infrastructure of climate-smart agriculture [47].

4.3. Edge–Cloud Computing and Big Data Analytics

Edge–cloud computing provides the computational infrastructure for distributed processing, analytics, and low-latency decision support in intelligent agriculture. As is demonstrated in **Figure 8** below, there are three interrelated layers in such a structure including physical layer, edge layer, and cloud layer [48]. The Physical Layer includes different types of smart devices placed throughout the agricultural environments, which include IoT Sensors, Drones, Greenhouses Monitoring Devices, Livestock Sensors, Farming Machines, Environmental Monitoring Devices, and others that keep on producing huge amounts of diverse data. These devices are connected to each other through wireless gateways and network infrastructure using communication technologies such as Wi-Fi, Bluetooth, Cellular Networks, and IoT [49].

The collected data from the field is transferred to the edge layer where the edge gateways conduct local processing and filtering of the data prior to its transfer to the cloud server. The edge-to-edge communication allows for fast transfer of information between different edge nodes, ensuring low network latency, less bandwidth utilization, and critical agricultural activities like irrigation management, plant disease detection, climate management in greenhouses, and coordination of autonomous machinery [50]. Whereas traditional cloud-based systems need inferencing and making decisions far away from the point of data generation, edge computing enables immediate inferencing and decision-making at the location of data generation. Edge computing is beneficial especially to big farms that require real-time monitoring for effective management of their farms [51].

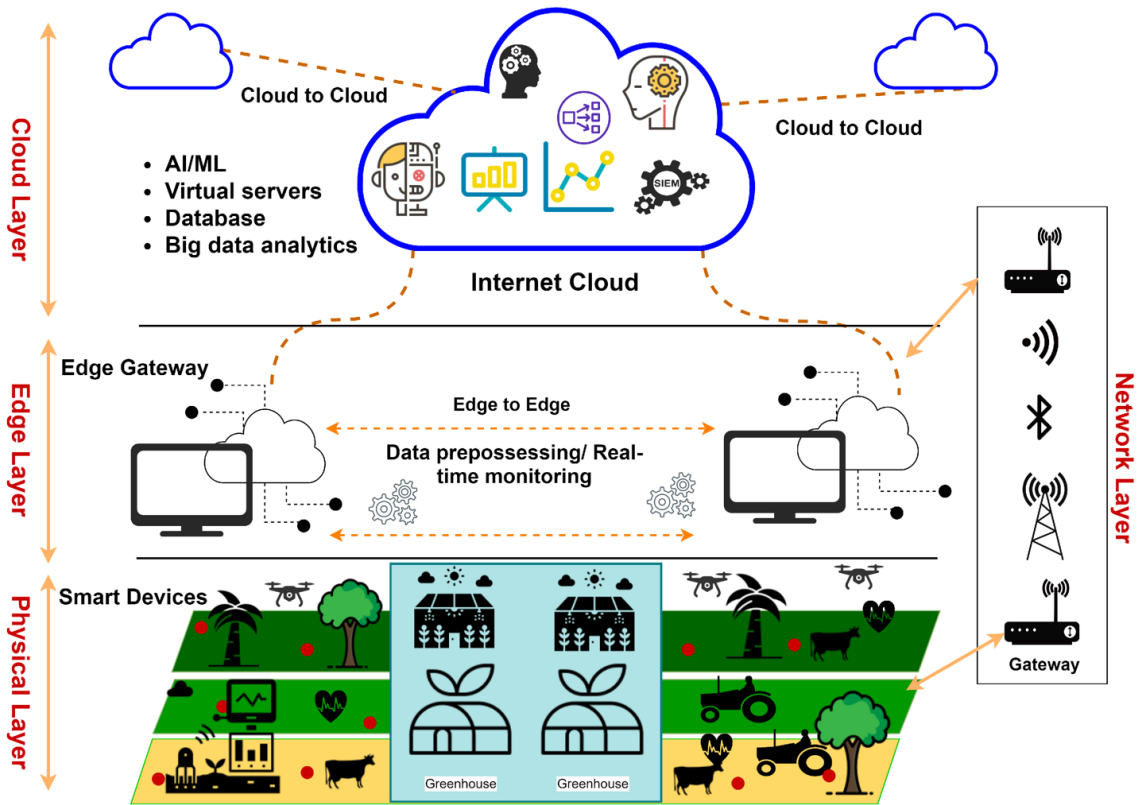


Figure 8. Edge-cloud computing architecture for AI-enabled smart agriculture and real-time farm monitoring.

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The cloud layer acts as the unified intelligence platform tasked with storage of data in the long term, creation of virtual servers, training of AI and machine learning models, as well as big data analytics. Cloud infrastructures collect the data collected by various edge devices to engage in prediction modeling, analysis of trends, resource optimization, and decision support service in crop, livestock, and greenhouses production. The data produced by AI models in the cloud are always in sync with the edge devices, thus creating an adaptive feedback loop [52]. In addition to this, communication between clouds makes it possible for the exchange of data between several agricultural platforms. As a result of this, the fusion of edge computing, cloud computing, and big data analysis creates a powerful computational platform that can support intelligent, data-driven, and climate-resilient agriculture [53]. Taken together, the reviewed studies demonstrate that no single sensing or computational technology is sufficient to address the complexity of farm-scale decision-making. The key research challenge therefore shifts from improving individual technologies to establishing interoperable architectures in which these complementary data streams can be integrated reliably and translated into timely management decisions.

4.4. Agricultural Data Ecosystems

Intelligent agriculture is becoming more reliant on the implementation of agricultural data ecosystems that leverage heterogeneous data sources, sensory technologies, communication channels, cloud-edge architectures, and artificial intelligence in order to facilitate data-driven decision-making throughout the agricultural production chain. Contemporary agricultural data ecosystems consistently produce structured and unstructured data from field-based sensors, UAVs, remote sensing satellites, weather stations, farm equipment, animal health tracking systems, greenhouse settings, and farm management systems [52]. The heterogeneous data sets are then aggregated using IoT communication channels, cloud-edge computing, big data solutions, and AI-based analytics. The interconnectivity of the above-discussed technologies facilitates smooth acquisition, storing, processing, visualization, and intelligent decision-making, increasing productivity, resource-use efficiency, and adaptability to climate change. **Table 2**

below provides an overview of the key data sources, enabling technologies, and respective applications in intelligent agricultural systems. From **Table 2**, it can be seen that each data source provides unique data for AI-powered agricultural systems while the enabling technologies mentioned above help convert raw agricultural data into meaningful knowledge [51].

Table 2. Data sources and enabling technologies for intelligent agriculture.

Data Source	Data Type	Enabling Technologies	Major Applications	Technological Maturity	References
IoT Sensors	Soil moisture, temperature, humidity, pH	IoT, Edge Computing, AI	Smart irrigation, environmental monitoring	Commercial Scale	Jararweh et al. [54]
UAVs	RGB, multispectral, hyperspectral, thermal images	Computer Vision, Deep Learning	Crop monitoring, disease detection	Pilot to Commercial Scale	Qazi et al. [55]
Satellites	Multispectral imagery, vegetation indices	Remote Sensing, GIS, AI	Crop mapping, drought monitoring	Commercial Scale	Prabha et al. [56]
Weather Stations	Rainfall, temperature, wind, humidity	IoT, Cloud Analytics	Weather forecasting, climate risk assessment	Commercial Scale	Shaikh et al. [57]
Agricultural Machinery	GPS, operational data, fuel usage	IoT, Precision Agriculture	Autonomous farming, machinery optimization	Pilot to Commercial Scale	Fuentes-Peñailillo et al. [58]
Livestock Sensors	Activity, body temperature, heart rate	Wearables, AI Analytics	Animal health and welfare monitoring	Pilot to Commercial Scale	Luo et al. [59]
Greenhouse Systems	Climate, CO ₂ , light intensity	IoT, Edge-Cloud Computing	Climate control, automated irrigation	Commercial Scale	Paul et al. [60]
Farm Management Systems	Farm records, operational data	Big Data, Cloud Platforms	Decision support, resource planning	Commercial Scale	Singh et al. [61]
Market & Supply Chain Data	Prices, logistics, demand	Big Data Analytics, AI	Supply chain optimization, market forecasting	Commercial Scale	Bissadu et al. [62]
Multi-source Data Integration	Structured and unstructured datasets	Digital Twins, Foundation Models, Multimodal AI	Intelligent decision support, predictive agriculture	Commercial Scale	Li et al. [63]

5. Applications of Intelligent Agriculture

5.1. Crop Production and Precision Farming

The processes of crop production and precision agriculture have been greatly revolutionized through the introduction of artificial intelligence, UAVs, IoT, and edge computing, thus making it possible to conduct intelligent monitoring and crop production with specific to each site. As shown in **Figure 9**, the process starts with the stage of data acquisition, where UAVs fitted with high resolution imagery sensors collect data about crop growth, canopy, diseases, and field variability during the entire cropping period [64]. Acquiring images continuously is very useful since it helps to get comprehensive spatial data that facilitates the early detection of any form of plant stress before any signs become visible. The acquired images are processed through noise removal, georeferencing, and data augmentation to increase the reliability of AI models [65].

In addition to preprocessing, sophisticated artificial intelligence models are utilized for disease detection and classification. These deep learning models automatically extract discriminating features from aerial images to detect various diseases, nutrient shortages, insect infestations, and other abnormalities in crops accurately. In addition, the use of XAI ensures greater transparency of the model by offering an explanation of AI decisions, which results in higher reliability and helps in making better decisions on the part of farmers and agriculture specialists [66].

The results derived from the analysis by the AI models are further incorporated with IoT and edge computing platforms for decision making in agriculture in real time. Through edge computing, the field data can be analyzed locally in order to minimize communication delays while responding quickly to the dynamic situation in the agricultural environment. This processed information is then provided using decision support systems such as heat maps, analytics reports, and mobile apps [67]. Intelligent recommendations allow for efficient pest control, irrigation, nutrient application, and continuous monitoring of crops, as well as minimize production expenses and adverse environmental effects. Thus, the integration of UAV-based imagery, artificial intelligence-powered analysis of crops,

Internet of Things, and edge computing provide a holistic approach to precision farming that enables data-driven and site-specific crop management to improve productivity and sustainability of agriculture [68].

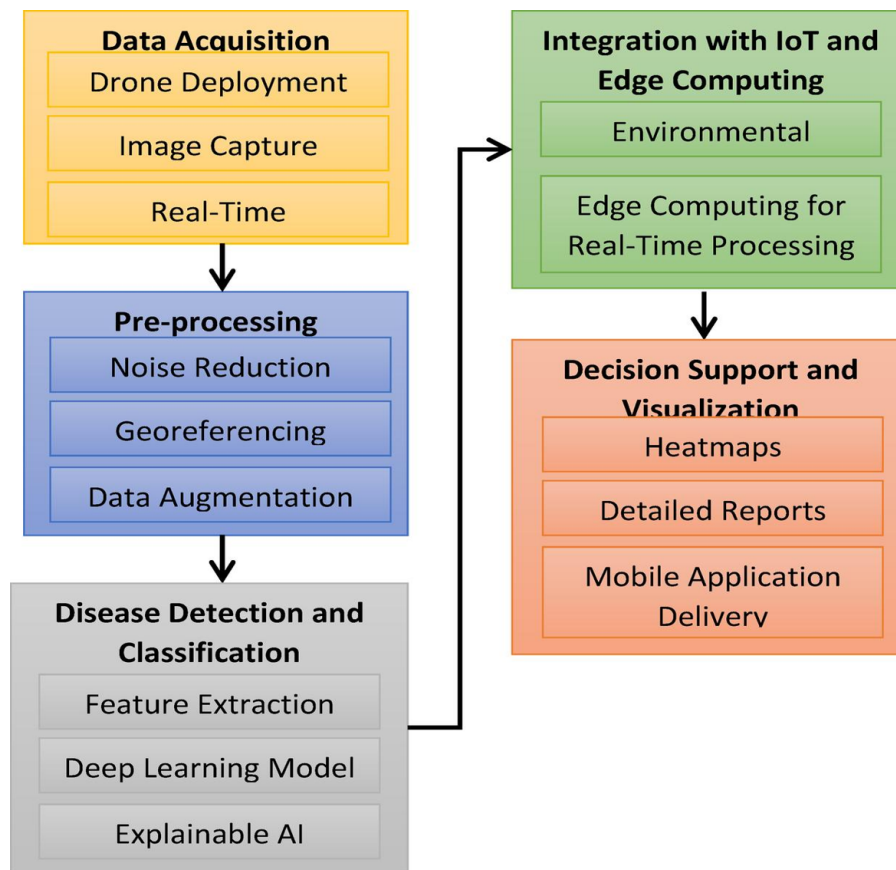


Figure 9. AI-based workflow for UAV-enabled crop disease detection and intelligent decision support.

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5.2. Soil, Water, and Climate Management

Smart farming has greatly changed soil, water, and climatic conditions through the use of sophisticated sensors, remote sensing devices, and artificial intelligence (AI) systems that facilitate real-time monitoring and decision-making capabilities. As shown in **Figure 10** below, information on agricultural operations is obtained from different levels of spatial dimensions through satellite systems, unmanned aerial vehicles (UAV), and plant sensors [69]. The multi-sensor model allows for constant monitoring of crop reactions to environmental stresses, involving droughts and heat stresses, which are the factors that pose limitations to agricultural production in changing climates. This combination of these different sensors will provide comprehensive data regarding the large-scale environmental variations and small-scale reactions of the crops to the environment [70].

The gathered data is processed by the use of an AI-based analytics approach to generate various critical indicators pertaining to the health of the crop and the stresses in its environment. Important physiological indicators like the canopy temperature, vegetation indexes, and chlorophyll fluorescence are extracted through multispectral, thermal, and optical sensing techniques to assess the performance of the crops in an unfriendly environment. The machine learning and deep learning approaches apply various datasets to diagnose the early stages of stress, predict water shortage, estimate the growth of crops, and assess the effect of climate variability before actual crop damage [71].

Integration of artificial intelligence, satellite-based remote sensing, unmanned aerial vehicles, and ground-sensing devices provides an integrated intelligent monitoring system for climate-resilient agriculture. The constant analysis of environmental and biological parameters by such systems helps to manage the water resources, assess

the condition of soil, evaluate climate risks, and develop sustainable agriculture plans [72]. In addition to that, the application of intelligent sensing together with AI analytics enables the ability to monitor the ecosystem changes over time and helps to allocate the available resources efficiently, build crop resilience to extreme climatic events, and produce sustainable food products. Thus, intelligent sensing, together with AI analytics, is an essential technical pillar for developing climate smart agriculture in the future [73].

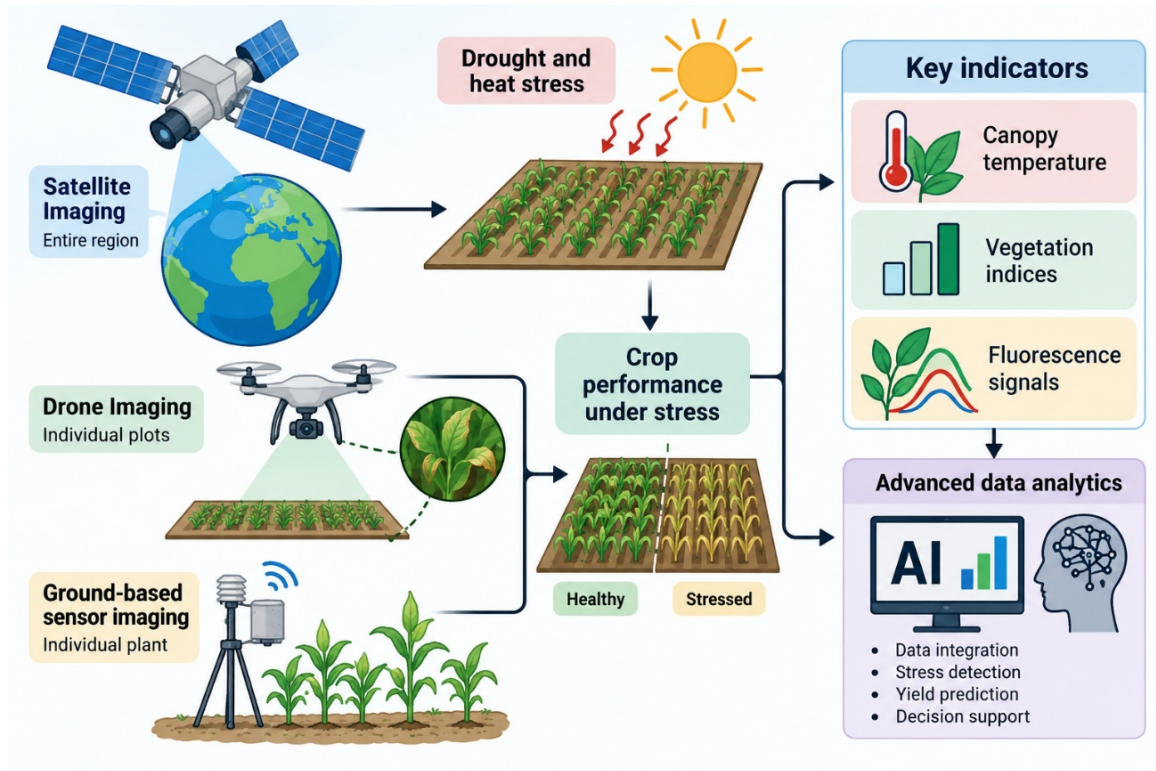


Figure 10. Multi-source remote sensing and AI framework for crop stress monitoring and phenotyping.

5.3. Livestock and Protected Agriculture

The advent of artificial intelligence (AI), IoT, and sensor technology has led to the modernization of livestock farming through the ability to continuously monitor the health, behavior, performance, and environment of the livestock. The intelligent livestock management system involves farm environment information (temperature, humidity, air quality, and light intensity), herd information (feeding, reproduction, health, and production), and animal information from sensors [74]. The analyses of these multimodal datasets are performed continuously using machine learning algorithms to monitor feeding activity, rumination, movement, body condition, reproduction, and early signs of disease. Compared with conventional periodic observation, continuous AI-assisted monitoring provides more timely detection of abnormal behaviour and health conditions, although its effectiveness depends strongly on sensor reliability, data quality, and the ability of models to generalize across breeds, production systems, and environmental conditions [75].

This intelligent information produced by livestock management systems can be combined with protected agriculture systems to develop full-fledged smart farming environments. Protected agriculture is similar to precision livestock farming since it involves the use of environmental sensors, IoT, and AI-based analytical algorithms to maintain ideal conditions of greenhouse temperature, humidity, CO₂ concentration, irrigation, and lighting [76]. The models of machine learning use environmental, sensor, and production data to develop intelligent decision-making systems that can support increasingly autonomous farm management. Compared with livestock-only or greenhouse-only monitoring, integrating the two domains enables coordinated interpretation of animal and environmental conditions, potentially improving resource-use efficiency and operational responsiveness. However, the benefits are highly dependent on real-time data integration, sensor coverage, and reliable model performance

under changing farm conditions [77].

5.4. Post-Harvest Management and Supply Chain Optimization

AI, IoT, and intelligent data structures have completely transformed post-harvest systems in terms of reducing losses that occur in quantitative and qualitative form during storage, transport, processing, and delivery. Post-harvest systems use IoT sensors along with computer vision, hyperspectral imaging, RFID tags, and wireless sensor networks to check for parameters such as temperature, humidity, ethylene, microbial infection, and quality of products [78]. These predictive models based on AI techniques process these datasets in real time to make predictions about the shelf life, spoilage, categorize the quality of the products, and even optimize their storage conditions for fruits, vegetables, cereals, and other perishable commodities. In addition, edge-cloud computing allows for real-time monitoring and instant decision making through processing the sensor data locally but simultaneously keeping the historical data synchronized on cloud-based computing systems. These smart monitoring systems are highly efficient in minimizing post-harvest losses [79].

The combination of AI and digital technologies has also revolutionized agriculture supply chain management through the provision of end-to-end visibility, traceability, and logistics. Analytics, blockchain, digital twins, and machine learning algorithms combine data from farms, storage centers, logistics networks, trading platforms, and consumer demands to optimize inventory management, routing, cold chain logistics, and market forecasts [80]. Moreover, computer vision and automated sorting technologies contribute to improved product grading, packaging and quality control by quickly detecting any defective or contaminated goods prior to delivery. Furthermore, AI-powered demand forecasting and decision-making systems facilitate dynamic pricing, production planning and effective resource management, which leads to lower operational expenses and reduced food waste. All these elements taken together result in creation of the data-driven agricultural system, which increases food security, economic efficiency, sustainability and resilience to the climate change through the effective distribution of agricultural produce from the field to the consumer [81]. Across these applications, the literature shows a clear progression from isolated AI-enabled tasks towards increasingly connected and automated agricultural operations. Nevertheless, most reported systems remain focused on a specific crop, sensing modality, or management function, limiting their transferability to whole-farm environments. The evidence therefore suggests that the next stage of intelligent agriculture should emphasize cross-domain data integration and coordinated decision-making rather than further optimization of isolated applications. Such integration is particularly important for climate-resilient farming, where crop, soil, water, weather, energy, and operational conditions must be considered simultaneously.

6. Autonomous Farming Systems

6.1. Agricultural Robotics and Autonomous Machinery

Autonomous agricultural robots and unmanned farming vehicles have become integral parts of the emerging generation of smart agriculture as a result of their capability of autonomously perceiving, navigating, decision-making, and performing tasks in a field with little human involvement. As seen in **Figure 11a**, contemporary agricultural robots are designed with sophisticated environmental perception sensors such as LiDARs, depth cameras, lasers, RGB cameras, GNSS/RTK, inertial measurement units (IMUs), and other intelligent sensors which constantly collect information about the environment around them. This data from multiple sensors creates high-resolution spatial and visual information helping robots perceive crops, obstacles, terrain features, and operational borders. The obtained information is further processed using intelligent navigation and environmental perception algorithms [82].

After sensing the environment, the robotic systems make a series of decisions that help to perform the tasks within their working environments. The process of decision making is hierarchical in nature and, as shown in **Figure 11b**, involves path-planning at the global and local levels, obstacle avoidance measures, and coordination among different robots. This decision process is controlled by the control level that utilizes a combination of traditional control systems, adaptive control, and intelligent control approaches to control robotic motion [83]. On the other hand, robotic systems utilize a variety of drive systems, which range from electric to hydraulic, pneumatic, or hybrid actuator systems coupled with mechanical manipulators and specific end-effectors to carry out tasks like harvesting, transportation of crops, spraying, seeding, picking fruits, and cutting activities. The use of sophisticated

perception, intelligence, and control increases efficiency and minimizes labor dependency [84].

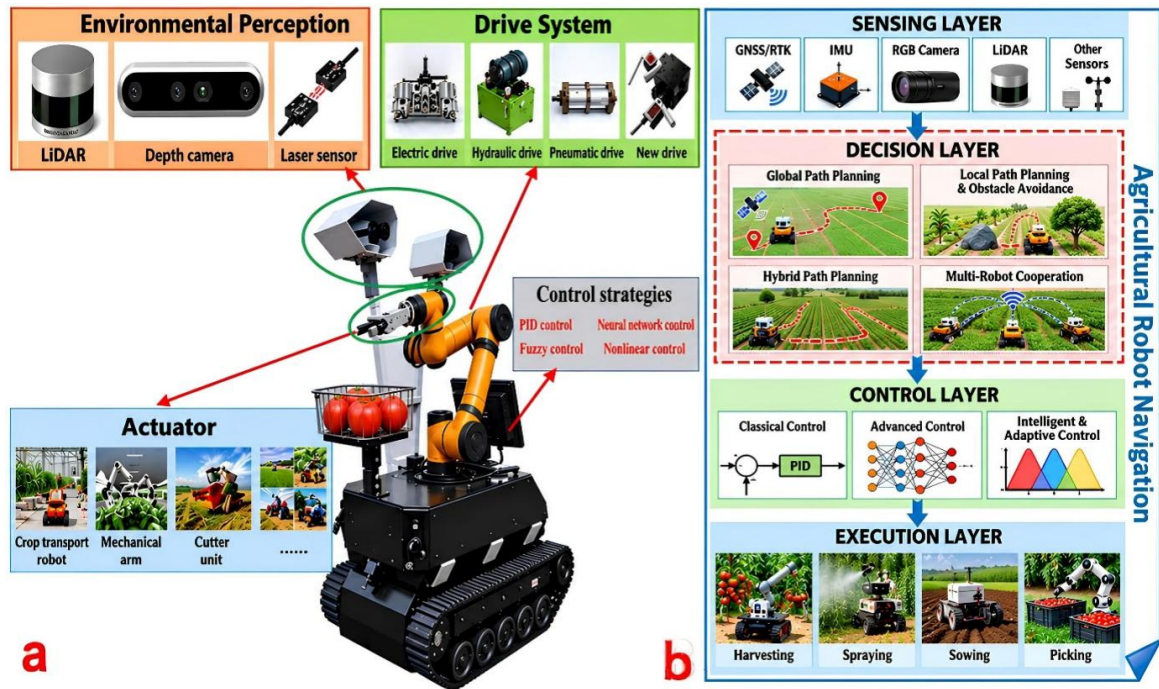


Figure 11. AI-enabled agricultural robot architecture and layered navigation framework for autonomous sensing, decision-making, control, and field operations: **(a)** Components and functional architecture of an autonomous agricultural robot, including perception, drive, control, and actuation systems (Reproduced from Xie et al. [82] under the copyright license CC-4.0); **(b)** Layered navigation framework integrating sensing, decision-making, control, and execution for precision agricultural tasks (Reproduced from Ye et al. [83] under the copyright license CC-4.0).

Execution is achieved by converting smart farming planning into agriculture practice through automated robotics that can perform repeated and manual laborious processes with precision and effectiveness. These automatic robots will work together within various agriculture settings to accomplish harvesting, precision spraying, planting, transporting of crops, and selective picking of fruits while adjusting themselves according to changes in their surroundings through real-time sensor input [85]. Artificial intelligence, computer vision, and machine learning technologies additionally augment the level of autonomy by allowing continuous learning, adaptive navigation, and efficient task execution in dynamic environments. As a result, robotics technologies in agriculture and autonomous systems represent the technological backbone of autonomous farming systems through the application of intelligent sensing, robotic perception, adaptive control, and automated field operations [86].

6.2. Smart Drones and Robotic Harvesting

Modern intelligent drones and robotic harvesting techniques are revolutionizing agricultural automation by making it possible to monitor crops accurately, detect fruits intelligently, and harvest them autonomously without any human assistance. As seen in **Figure 12** below, modern robotic harvesting machines employ machine vision, autonomous mobility, robotic manipulators, and intelligent end effectors to carry out efficient harvesting [87]. Vision system with high-resolution RGB and depth cameras like Intel RealSense D455 is constantly capture images of the crop canopy and detecting ripe fruits or harvest targets through the application of AI and computer vision algorithms. These algorithms are able to detect 3D location, maturity level, and the best place to make a cut for individual fruits [88].

Once the targets have been identified, the robot autonomously moves the SCARA robotic arm attached to a crawler mobile base to perform harvesting operations in different field conditions. The SCARA robotic arm uses an end-effector equipped with a disc knife to precisely cut the grapes and collect in the storage bin attached to the robot using an automated lifting system. The crawler mobile base allows autonomous navigation of the robot within

the orchard/vineyard for harvesting of several plants simultaneously [89]. In parallel, intelligent drones that are fitted with sensors such as RGB, multispectral, hyperspectral, and thermal sensors enhance the process of robotic harvesting through mapping large farms, detecting stress within crops, assessing maturity levels of fruits, mapping yields, and identifying ideal harvesting zones prior to sending robots on the ground [90].

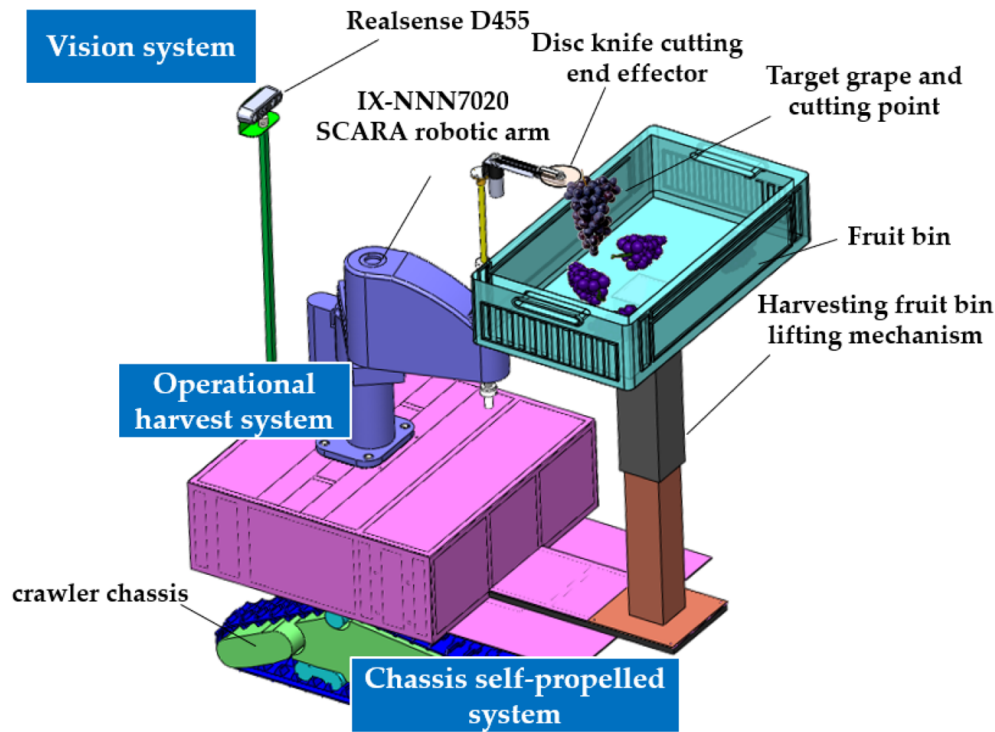


Figure 12. AI-enabled autonomous robotic system for precision grape harvesting.

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Combining technologies of artificial intelligence, robotics, computer vision, and automatic navigation, is an increasing trend towards achieving full autonomy in agriculture. The models of perception using AI constantly analyse the visual data and enhance the process of object recognition, obstacle detection, and harvesting process, whereas robotics control systems adjust the movement and cutting process in real-time [91]. Data obtained through harvesting operations are additionally analyzed through cloud computing and farm management systems to aid in yield prediction and productivity assessment as well as make predictive decisions about future crops. Thus, the synergy between smart drones and autonomous harvesters presents a scalable intelligent technology for tackling the shortage of labor in farming and lowering the costs of harvest and improving its quality [92].

6.3. Human-AI Collaboration

Human-AI collaboration is one of the upcoming paradigms in autonomous agriculture systems due to the combination of human expertise and analysis power of AI. The collaborative paradigm starts from data collection continuously through the use of IoT sensors and surveillance system in UAVs. This collects data on the phenotypic behavior of crops, soil conditions, nutritional condition of the farm, and other environmental factors [93]. These multisource datasets are analyzed using AI tools to identify crop stress, nutrient deficiencies, and environmental hazards that may be less readily detected through conventional field inspections. Compared with manual observation alone, AI-assisted analysis can provide faster and more consistent interpretation of large and heterogeneous datasets; however, its performance remains sensitive to data quality, environmental variability, and model generalization. Therefore, human expertise remains particularly important for validating AI recommendations and adapting them to site-specific agronomic conditions [94].

The analyzed information is combined with human expertise and on-field experience in order to provide adap-

tive farm management and resource optimization. Information produced through AI will help farmers choose appropriate agronomic measures, optimize use of bio stimulants, improve crop performance and increase resource-use efficiency. Feedback continuously collected from on-field observations will refine AI algorithms and create an adaptive cycle of learning which will lead to increased prediction accuracy and management decisions. This collaboration between human intellect and AI algorithms will not only boost the efficiency of agriculture but will make agriculture more resilient to climate change through timely and data-driven decisions made in a transparent way and under human control [95].

6.4. Toward Autonomous Farm Ecosystems

The move towards autonomous farm ecosystem is going to be the next phase of intelligent agriculture as the use of artificial intelligence, autonomous agents, and optimization processes will lead to self-adaptive farm management that requires very little human supervision. Autonomous farming makes use of the multi-agent learning process that learns from the existing agricultural knowledge as well as from current farm observations in order to achieve efficient operation. Reinforcement learning algorithms such as DQN and PPO can train the agents to develop optimal management strategies [96]. These smart agents constantly take into account various aspects, like growth stages of crops, irrigation, climatic variations, water usage, energy usage, land conditions, and crop yield, while at the same time balancing the environment, economic, and operational considerations. Combining optimization algorithms with data management and feature fusion through the blockchain approach increases the effectiveness of the decision-making process [97].

Decision-making policies within the autonomous farm ecosystems keep improving using real-time feedback and learning processes. Various intelligent agents share information, adjust policies, and synchronize agricultural operations depending on the changing environment and seasons. This ensures that the irrigation, energy use, resources allocation, and crop production become dynamically optimized due to the changes taking place. Autonomous ecosystems differ from traditional precision agriculture systems because the former utilize continuous learning process for the sake of enhancing efficiency through low energy use, low carbon emission, optimal water use, and high crop yield [98]. The dynamic relationship between reinforcement learning algorithms, optimization techniques, and real-time agricultural data results in the emergence of a self-learning agriculture ecosystem that can engage in autonomous planning, flexible resource allocation, and robust decision-making. It is anticipated that such self-governing agricultural systems will be very instrumental in establishing sustainable, climate-adaptive, and highly-efficient agricultural practices [99]. The reviewed evidence suggests that autonomous agriculture is evolving from rule-based automation towards adaptive systems capable of learning from continuous farm feedback. However, the transition to fully autonomous farm ecosystems requires more than reinforcement-learning algorithms or intelligent agents alone. It depends on the coordinated availability of reliable real-time data, interoperable sensing and communication infrastructure, trustworthy AI models, and mechanisms for human supervision. Thus, autonomy should be considered as an integrated system-level capability rather than as a property of an individual algorithm or device.

7. Integration Framework for Next-Generation Agriculture

7.1. AI-Foundation Model-Digital Twin Convergence

The fusion of artificial intelligence (AI), foundation models, and digital twins is a revolutionary approach towards intelligent agriculture in the future, since all the functions of perception, inference, prediction, and autonomous decision making are combined into one cyber-physical system. AI technology is equipped with sophisticated tools for analyzing big data in the agricultural sector, while foundation models are trained on a wide variety of multi-modal data including text, images, sensor feeds, satellites, weather, and field management data [100]. The concept of digital twin technology serves as an extension to these features through the generation of a dynamic model of the physical systems, which is constantly updated based on real-time data gathered using IoT sensor technologies, unmanned aerial vehicles, remote sensing devices, and wireless communication. The combination of these technologies facilitates the continuous monitoring, simulation, evaluation, and optimization of agricultural systems through the use of virtual environments [101].

Intelligent interactions among AI, digital twin, and foundation models lead to an intelligent agriculture sys-

tem that is able to learn and make decisions resilient to climate change. Digital twins are improved by the use of foundation models because they provide reasoning, multimodal data fusion, and zero-shot or few-shot learning, while AI updates them using analytics [102]. At the same time, feedback from digital twins is used by AI systems to improve the predictive model for effective management of irrigation, fertilizers application, disease prevention, greenhouses management, and self-driven machines in the field. All this leads to increased precision, operational efficiency, optimization of the use of resources, sustainability, and decreased dependency on human input. Thus, the integration of AI, foundation models, and digital twins lays the technological base for next-generation agriculture, allowing for creating adaptive and autonomous farming systems [103]. The significance of this convergence lies in the complementary roles of the three technological layers: AI enables perception and prediction, foundation models provide broader multimodal reasoning and knowledge integration, while digital twins provide a dynamic representation of the physical agricultural system. Their integration can therefore create a feedback loop in which real-world observations inform virtual simulations and the resulting predictions guide physical farm operations. However, such a framework also introduces challenges related to data interoperability, model reliability, computational requirements, cybersecurity, and validation across different agricultural environments. As these technologies are developing rapidly, the evidence reported in recent studies should be viewed as an evolving knowledge base, and further field-scale validation is required before their long-term performance and generalizability can be established.

7.2. Intelligent Decision Support Systems

IDSS stands for Intelligent Decision Support Systems and forms the heart of future agriculture technologies because of its incorporation of artificial intelligence (AI), digital twins, foundation models, IoT, remote sensing, and big data analysis into a single decision-making process. IDSS uses data gathered from various sources, including sensors from fields, unmanned aerial vehicles (UAV), satellites, meteorology centers, farm machinery, and historical databases of agriculture, to provide recommendations on the management of farms [104]. Through the use of advanced AI technologies like machine learning, deep learning, explainable AI, multimodal foundation models, and generative AI, the identification of intricate spatio-temporal patterns from multi-source data becomes possible, allowing for applications like crop health estimation, disease detection, irrigation planning, fertilizer optimization, yield prediction, and climate change prediction. Using predictive analysis along with constant environmental monitoring, IDSS helps convert raw agriculture data into information that is useful to make better management decisions [105].

The incorporation of digital twins and autonomous AI technologies takes the ability of intelligent decision support systems a step further through real-time simulation and optimization prior to practical applications on the ground level. The use of digital twins involves continuous synchronization between the virtual farm and actual environmental circumstances, enabling farmers and others to test out various approaches under various conditions [106]. At the same time, reinforcement learning and agentic artificial intelligence self-improve the decision-making policy in light of continuous feedback, making resource allocation, performance, and resilience better in each subsequent production cycle. Explainable artificial intelligence increases the transparency of the process by delivering interpretable decisions to users, which increases their trust in this solution and makes it easier to apply in precision farming. As a result, intelligent decision-support systems constitute the core computing architecture of future agriculture [107].

7.3. Proposed Next-Generation Intelligent Agriculture Framework

Next generation intelligent agriculture would need a unified approach that brings together all the sensing technology, artificial intelligence (AI), cloud-edge computing, and digital twins to achieve autonomous, data-driven, and climate-smart farming operations. As shown in **Figure 13**, the approach to be employed involves starting from the physical level in which heterogeneous data are acquired from the field through IoT-based sensing, camera, drone, and satellite-based remote sensing technology [108]. The various sensing platforms capture essential information regarding the environmental parameters and crop status such as soil pH levels, soil moisture content, soil temperature, environmental conditions, plant growth, pests, and diseases. The combination of ground-based sensors with aerial and satellite sensors helps in capturing spatial and temporal data that create the digital replica of the agricultural environment. Such data collection forms the base for intelligent agricultural analytics [109].

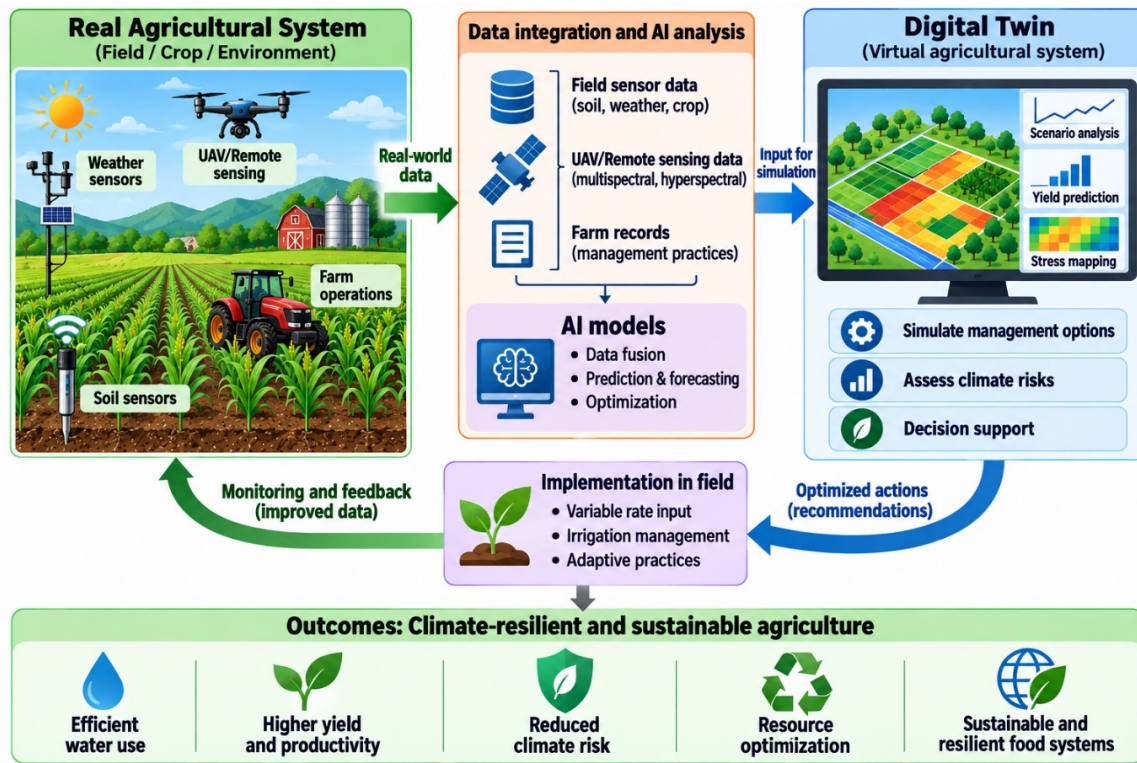


Figure 13. Digital twin framework integrating IoT, edge computing, cloud AI, and remote sensing for smart agriculture.

The acquired data is sent to edge computing systems where they are processed, filtered, and features extracted before being sent to cloud computing infrastructure for storage and analytics. The cloud computing system uses AI for data processing, big data analytics, 3D modeling, and simulation to create digital twins of the agriculture system. This creates a virtual model that replicates the real-time status of the agricultural environment [110]. The algorithms developed in the AI system will analyze multisource data sets for identifying crop stresses, predicting disease epidemics, optimizing irrigation schedules, assessing management practices, and predicting crop performance under different environmental conditions. The exchange of information between the cloud-based digital twin and the physical farm system will create a feedback loop that is referred to as cyber-physical system [111].

This framework for the future represents a departure from the traditional paradigm of precision agriculture as it integrates adaptive intelligence and continuous learning with autonomous decision-making support. Using the technologies such as the Internet of Things (IoT), remote sensing, edge-cloud computing, artificial intelligence (AI) and digital twins, the framework is able to provide real-time monitoring and predictive modelling [112]. Moreover, this architecture lays down a scalable framework to integrate new technologies like foundation models, multimodal artificial intelligence, generative artificial intelligence, and agentic artificial intelligence that would help improve contextual awareness, autonomous reasoning, and human-AI teamwork in future farming applications. Therefore, the proposed architecture is a complete roadmap to design an intelligent, sustainable, and climate resilient agriculture system [113].

7.4. Practical Implementation Strategies

The adoption of next-generation intelligent agriculture is possible by adopting an evolutionary and holistic process where the latest technologies and the current farming practices are combined. The first step of this evolutionary process must include the building of a solid infrastructure in the form of IoT sensors, wireless communication networks, UAVs, remote sensing satellites, and edge to cloud computing systems [114]. The standardization of the process of collecting data, communication interoperability, and cloud storage of data in a secure manner are critical for the seamless integration of heterogeneous agricultural data. Following this step, it is vital to incorporate

technologies such as AI, foundational models, multimodal learning and digital twins to facilitate predictive analysis, simulation of crops in virtual settings, decision-making and precision management of resources. Creating scalable digital twin platforms which can synchronize the physical farm with the virtual farm continuously would allow for real-time monitoring and analysis [115].

Implementation is not only about technology but also about effective governance systems, participation of all stakeholders, and capacity building for farmers and agricultural experts. The government, along with various other organizations, should cooperate and form policies such as data openness and security standards, cybersecurity laws, and AI ethics [116]. Investments in infrastructure development, cost-effective sensing equipment, internet availability in rural areas, and educational schemes to train farmers can play equally critical roles in fast-tracking the adoption of the technology, especially in resource-scarce environments. In addition, pilot demonstration farms, public-private collaboration, and rigorous testing of AI and digital twins' models in various agro-climatic zones will increase system reliability and confidence. Together, all these strategies will contribute to the deployment of large-scale intelligent agricultural ecosystems that will help improve productivity and resource management and boost climate resilience and sustainable food production [117].

8. Challenges and Future Research Directions

Despite substantial progress, several cross-cutting research gaps continue to limit the practical deployment of intelligent agriculture. A major gap concerns the integration of heterogeneous agricultural data generated from IoT sensors, remote sensing, weather observations, farm operations, and other sources. Future studies should focus on interoperable data structures, domain-specific datasets, standardized benchmarks, and robust validation protocols to improve the generalizability of AI and foundation-model-based systems across crops, regions, and agro-climatic conditions. In particular, the key problem of the current state of intelligent agriculture is that agricultural data produced by a variety of sources are heterogeneous. These data vary in spatial and temporal resolution, in format, in quality and in semantics [118,119]. A second major gap is the limited development and validation of integrated farm-scale digital twins. Most existing implementations remain application-specific, creating a need for scalable architectures capable of synchronizing crops, soil, climate, machinery, livestock, and farm operations within a common virtual environment. Research should therefore prioritize semantic interoperability, standardized digital-twin frameworks, real-time synchronization, scalability, and multi-site field validation rather than focusing only on individual agricultural assets.

Some other challenges that need to be considered are related to infrastructure, governance, cybersecurity, and proper use of AI. There is an increasing dependence on cyber-physical systems, and hence, there are worries about data security and data ownership, etc. [120]. There is very little transparency within the black box type of AI systems, making farmers less likely to trust autonomous decision-making algorithms. Therefore, the development of explainable AI, transparent decision support systems, uniform data governance, and cybersecurity measures is crucial in ensuring that intelligent agriculture technologies are used responsibly. In addition to that, poor digital literacy and lack of unified international standards also contribute to the delayed use of technology [121].

Future studies need to transcend the development of fragmented technology and proceed towards fully integrated, smart agricultural ecosystems combining foundation models, multimodal AI, digital twins, explainable and agentic AI, robotics, edge-cloud computing, and advanced wireless communication systems including 6G. Self-learning digital twins, which continuously adapt using reinforcement learning and multimodal reasoning, can be seen as a promising trend [122]. The future systems should also focus on federated learning, privacy-preserving AI, trustworthy foundation models, semantic interoperability, and standardization of digital twin frameworks which allow for seamless exchange between different agricultural systems. Additionally, the integration of climate forecasting, carbon accounting, biodiversity monitoring, and circular bioeconomy in intelligent agricultural systems would ensure sustainable resource use and climate resilience. Lastly, field validation at scale, agricultural data openness, interdisciplinarity, and policy making would be instrumental in accelerating the shift towards resilient, autonomous, interpretable, and sustainable Agriculture 6.0 [123]. These challenges are interdependent rather than independent barriers. For example, heterogeneous data can limit model reliability, limited interoperability can prevent effective digital-twin integration, and inadequate cybersecurity can restrict the sharing of data across connected farm systems. Similarly, technical advances alone may not result in adoption when farmers lack the digital skills, infrastructure, or confidence required to interact with AI-driven decision-support systems. Therefore, future

research should address intelligent agriculture as a socio-technical system in which technological performance, data governance, infrastructure, human capabilities, and institutional frameworks are developed together.

9. Conclusions

The challenges posed by climate change, rising food needs, and shortage of resources are radically changing modern agriculture and are making it imperative to design intelligent and climate-resilient agricultural systems. The aim of this review was to provide an exhaustive analysis of the combination of artificial intelligence (AI), foundation models, digital twin, intelligent sensing systems, and autonomous agriculture as the technology behind future intelligent agriculture. In contrast to traditional review studies which have analyzed these technologies separately, this study has provided an integrated perspective highlighting how AI analytics, foundation models, digital twins, IoT sensing, edge-cloud computing, remote sensing, and autonomous robotics form a cyber-physical agricultural system.

The review highlighted that conventional machine learning has evolved toward explainable, generative, and agentic AI, while foundation models provide generalized reasoning capabilities across heterogeneous agricultural data, including text, images, sensor observations, weather information, and geospatial datasets. Simultaneously, digital twins enable dynamic synchronization between physical farms and virtual environments, allowing real-time simulation, adaptive resource management, and predictive optimization under changing climatic conditions. Furthermore, intelligent data infrastructures integrating IoT, wireless sensor networks, UAVs, satellite observations, and edge-cloud computing provide the computational backbone required for scalable and real-time agricultural intelligence. These technological advances collectively enhance crop productivity, improve resource-use efficiency, reduce environmental impacts, strengthen climate resilience, and support sustainable food production.

However, many barriers still need to be overcome for intelligent agriculture to become a reality on a broad scale. These include problems such as heterogeneity in the integration of data, interoperability of digital technologies, complexity of the foundational models, cybersecurity, privacy, lack of benchmarks, lack of interpretability of models, and a lack of standards for digital twins. Resolving these problems would require collaboration from different disciplines of experts, including agricultural scientists, computer scientists, engineers, policymakers, and industry representatives.

In the future, intelligent agriculture would advance to become completely autonomous, self-learning, and co-operative agricultural ecosystems where multimodal foundation models, agentic AI, digital twins, robotics, and next-generation communication technologies work together for adaptive farm management in real-time. In future research, federated learning, privacy-preserving learning, explainable AI, trustworthy AI, multimodal reasoning, semantic interoperability, carbon-based decision support systems, and climate change-adaptive digital twin frameworks that would allow integration of biological, environmental, and socio-economic factors in the whole agricultural process should be a priority. All the advancements would help in advancing from precision agriculture to Agriculture 6.0.

Author Contributions

Writing original draft, conceptualization, investigation, K.K.; investigation, writing, data curation, corrected the Ms properly, A.K.; carried out initial planning, conceptualization, supervision, visualization, writing, editing, and reviewing, I.S.T. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable. This study did not involve humans or animals, and therefore ethical approval was not required.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data and materials presented in the manuscript or additional supporting files and formats have not been taken from publicly available repositories. All the authors agreed to provide data and materials after request.

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Conflicts of Interest

The authors declare that they have no known competing financial or non-financial interests or personal relationships that could have appeared to influence the work reported in this paper.

AI Use Statement

During the preparation of this manuscript, the authors used ChatGPT solely for graphic design polishing and language refinement. The authors declare that no artificial intelligence (AI) tools were used in the preparation of these manuscripts. The content and data in the graphics are from the authors; AI is only used for formal visualization, polishing and language refinement.

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