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Digital agriculture through AI and drone technology: Opportunities and challenges for agribusiness management

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ABSTRACT

Digital agriculture is transforming agrifood systems by integrating artificial intelligence (AI), unmanned aerial vehicles (UAVs), remote sensing, Internet of Things (IoT), big-data analytics and digital decision-support systems into agribusiness operations. This review synthesizes the applications, opportunities and challenges of AI- and drone-enabled digital agriculture, with emphasis on agribusiness management. A *meta-analysis* of 52 studies involving 32,400 participants reported a pooled digital-farming technology adoption rate of 38.95%, highlighting variability in technology uptake. Machine learning, deep learning and computer vision are increasingly applied to yield prediction, disease and pest detection, weed identification, crop monitoring, plant phenotyping, fruit detection, irrigation management, quality assessment and agricultural forecasting. UAVs equipped with RGB, multispectral, hyperspectral, thermal and LiDAR sensors provide spatial information that can be processed by AI models to generate actionable intelligence. Their integration creates a pathway from data acquisition and image processing to prediction, decision support and precision intervention. These technologies offer opportunities to improve resource-use efficiency, reduce input and labour costs, strengthen risk management, enhance productivity and support production, supply-chain, marketing and profitability decisions. However, adoption remains constrained by high investment costs, inadequate connectivity, limited digital skills, data-quality and interoperability issues, cybersecurity, privacy, regulatory requirements and uncertainty regarding AI reliability and explainability. Evidence from 27 case studies emphasizes infrastructure, financial and digital-literacy barriers for small-scale producers. Future progress will require affordable service models, responsible data governance, field validation and collaboration among farmers, technology providers, agribusinesses and policymakers. AI- and drone-enabled digital agriculture can support precise, predictive, resilient, sustainable and profitable agribusiness systems.

Keywords: Artificial intelligence, Digital agriculture, Drones, Machine learning, Precision agriculture, Remote sensing

1. Introduction

Agriculture is undergoing a profound digital transformation in which conventional production systems are increasingly being complemented by data-driven technologies, automated decision-making and interconnected information systems. Digital agriculture broadly encompasses the use of digital technologies to collect, store, process, analyse and exchange information throughout agricultural production and the wider agrifood value chain. This transition represents an evolution from conventional and precision agriculture towards more integrated forms of smart and digital farming, where information from farms, markets, weather systems, sensors and remote-sensing platforms can be combined to support timely and location-specific decisions. The development of Internet of Things (IoT) devices, cloud computing, artificial intelligence (AI), robotics, remote sensing and unmanned aerial vehicles (UAVs) has substantially expanded the ability of agricultural stakeholders to generate and use high-volume, high-resolution data. Wolfert *et al.* (2017) [1] emphasized that big data and connected technologies are not restricted to field-level operations but can influence farm management, business processes and the broader food supply chain. Similarly, Klerkx *et al.* (2019) [2] highlighted that digitalization is reshaping agricultural production systems, value chains and food systems by introducing technologies such as IoT, artificial intelligence, robotics, ubiquitous connectivity and digital platforms. More recent evidence indicates that digitalization is increasingly being positioned as a mechanism for improving the efficiency, sustainability and resilience of agrifood systems rather than simply as a technological upgrade of farm machinery (Shamshiri *et al.*, 2024) [3].

The increasing complexity of modern agribusiness further strengthens the need for digital decision-support systems. Contemporary agribusiness extends well beyond primary crop and livestock production and encompasses input supply, farm operations, processing, storage, logistics, marketing, finance, insurance and consumer-oriented value chains. Managers must therefore make decisions under conditions of uncertainty in

volving fluctuating input prices, market volatility, weather variability, changing consumer preferences, resource limitations and increasingly stringent environmental requirements. In such an environment, conventional decision-making based primarily on historical experience and periodic field observations may not provide sufficiently timely or spatially precise information. Digital agriculture can generate continuous streams of information and transform them into actionable intelligence for production and business management. In particular, AI-based systems can analyse heterogeneous datasets, identify patterns, predict future outcomes and provide recommendations for management decisions. *Khanna et al. (2024)* [4] noted that AI-based agricultural technologies have the potential to improve measurement, prediction and site-specific management while also changing the economic decision space surrounding technology adoption. Thus, the significance of digital agriculture extends beyond increasing farm productivity; it increasingly concerns the ability of agribusiness enterprises to manage information, resources, risks and value-chain operations more efficiently.

At the same time, agriculture faces a combination of climate, labour and resource-related constraints that make efficient management increasingly important. Climate variability and extreme events such as droughts, heat stress, excessive rainfall and floods can alter crop growth, pest and disease dynamics and ultimately farm profitability. Agricultural systems are also confronted with limitations in water availability, soil resources, energy and other production inputs, while labour shortages and rising labour costs create additional pressure for mechanization and automation. Digital and automated technologies can help address these constraints by improving the precision and timing of agricultural operations. The Food and Agriculture Organization (FAO) has reported that digital and automation solutions can contribute to overcoming labour bottlenecks, improving productivity, resilience and efficiency, and reducing environmental pressures, although adoption remains constrained by investment costs, digital skills, connectivity and enabling institutional conditions, particularly among small-scale producers (*McC Campbell, 2022*) [5]. These challenges create a strong rationale for technologies capable of rapidly observing field conditions, identifying spatial variability and supporting timely interventions.

Among the technologies driving this transformation, AI, IoT, remote sensing and UAVs are particularly important because they complement one another across the agricultural data cycle. IoT systems and field sensors can continuously generate information on soil, weather, crops and farm operations, while satellite and remote-sensing technologies provide broader spatial observations. UAVs or agricultural drones can complement these sources by acquiring high-resolution, field-level information using RGB, multispectral, hyperspectral and thermal sensors. AI and machine-learning algorithms can subsequently process these complex datasets to identify crop stress, detect diseases and weeds, estimate biomass and yield, classify field conditions and support precision management. Recent reviews demonstrate increasing integration among AI, IoT, UAVs, machine learning, deep learning and wireless communication technologies within smart-farming systems (*Makam et al., 2024; Shamshiri et al., 2024*) [6, 7]. UAV-based sensing is particularly valuable because it provides flexible, rel-

atively high-resolution and timely observations, while AI provides the analytical capability required to convert large volumes of imagery into useful agricultural information. *Wang et al. (2024)* [8] further identified the combination of UAVs and deep learning as an important direction in precision agriculture, particularly for image-based agricultural monitoring and decision support.

The integration of AI and drone technology is therefore more significant than the independent application of either technology. A drone can efficiently acquire detailed information from agricultural fields, but the practical value of that information depends on the ability to process and interpret it rapidly. Conversely, AI algorithms require reliable and representative data to generate accurate predictions and recommendations. Their integration establishes a digital decision pipeline in which UAVs acquire field-level data, AI algorithms interpret the data, predictive models generate intelligence, and management systems convert that intelligence into operational decisions. Such a framework can support site-specific irrigation, nutrient management, disease and pest surveillance, weed identification, crop stress assessment, yield prediction and targeted chemical application. The resulting benefits can extend from farm production to agribusiness management through improved input allocation, reduced operational costs, better risk assessment, improved harvest planning and more reliable production forecasts. Recent research on AI-enabled agriculture similarly emphasizes the potential of AI to improve measurement, prediction and site-specific management, while drone-focused studies demonstrate the growing role of UAVs in precision crop monitoring and agricultural automation (*Khanna et al., 2024; Makam et al., 2024*) [4, 9].

Despite these technological advances, the transition towards AI- and drone-enabled agriculture is not without challenges. The benefits of digital technologies depend on the availability, quality and interoperability of data, reliable connectivity, technical expertise, appropriate infrastructure and economically viable business models. AI systems may also face problems associated with limited training datasets, model generalizability, interpretability and algorithmic bias. Drone deployment can be constrained by acquisition and maintenance costs, battery capacity, payload limitations, weather conditions, regulatory requirements and the availability of trained operators. At the institutional level, concerns regarding data ownership, privacy, cybersecurity, technology standards and unequal access can influence adoption and the distribution of benefits. *Wolfert et al. (2017)* [1] identified data quality, integration, ownership, privacy, security, analytics and business models as important issues in the development of data-driven farming systems. More recent evidence similarly indicates that adoption of digital agriculture is shaped not only by perceived profitability but also by trust, usability and institutional factors (*Yeo et al., 2024*) [10]. These challenges are particularly important in developing agricultural economies, where fragmented landholdings, limited digital infrastructure, inadequate technical capacity and financial constraints may restrict access to advanced technologies. FAO evidence indicates that high investment costs, limited digital skills and inadequate enabling environments remain major barriers to inclusive digitalization, especially for small-scale producers.

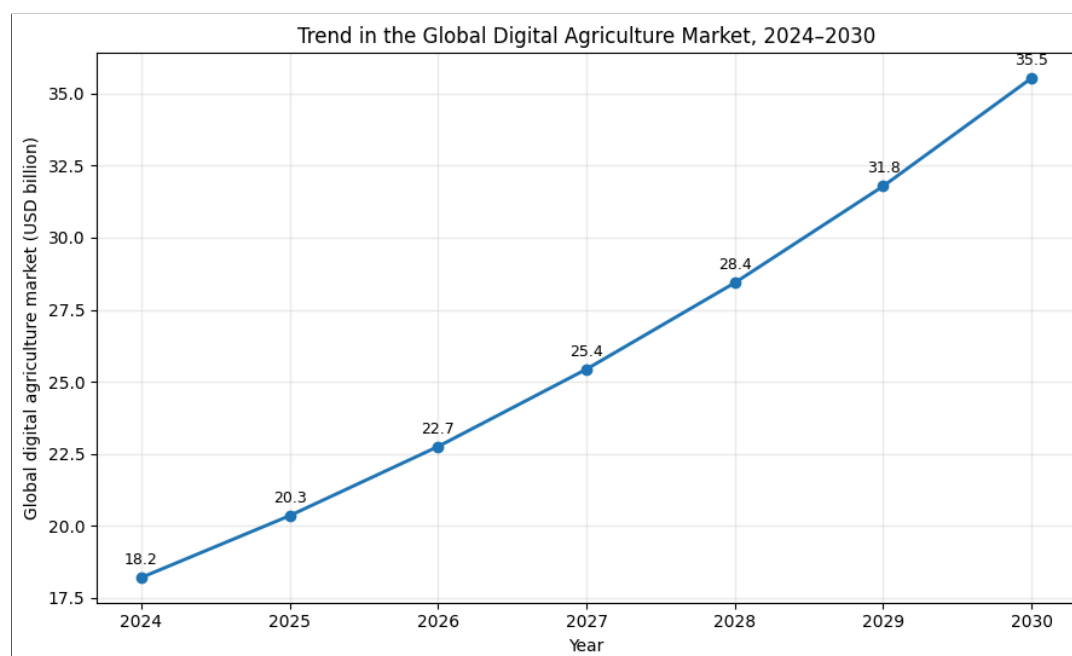


Figure 3. Trend in the Global Digital Agriculture Market, 2024–2030

Although a substantial body of literature has examined digital agriculture, AI, UAVs, precision agriculture and smart farming individually, there remains a need for a more integrated assessment of how AI–drone convergence can influence agribusiness management across the agricultural value chain. Existing reviews have extensively discussed technical applications of UAVs, AI-based crop monitoring and digitalization for sustainable production, but comparatively less attention has been given to connecting these technologies with the broader managerial dimensions of agribusiness, including cost management, production planning, risk management, supply-chain coordination, market intelligence, financial decision-making and business-model development. For example, recent reviews have synthesized the technical potential of UAVs and deep learning in precision agriculture (Wang *et al.*, 2024) [8], while other studies have examined the broader digitalization of agricultural production and its economic and environmental implications (Shamshiri *et al.*, 2024) [3]. The emerging economic literature on AI adoption further suggests that the implications of these technologies extend to farm profitability, resource allocation, incentives and equity, indicating the need to examine digital agriculture from both technological and managerial perspectives (Khanna *et al.*, 2024) [4].

Against this background, the present review examines digital agriculture through the integration of artificial intelligence and drone technology, with particular emphasis on opportunities and challenges for agribusiness management. The review aims to synthesize current knowledge on the evolution of digital agriculture and the complementary roles of AI and UAV technologies; critically assess their applications in crop monitoring, resource management, production forecasting, risk assessment and agricultural decision-making; examine their implications for farm economics, supply chains, marketing and other agribusiness functions; identify technological, economic, institutional, regulatory and social barriers to adoption; and discuss emerging business models and future research directions for inclusive and sustainable digital agriculture. By bringing together the technological and managerial dimensions, this review seeks to provide a comprehensive perspective on how AI- and drone-enabled systems can move agriculture from data generation towards data-driven agribusiness intelligence, improved decision-making, greater resource-use efficiency, enhanced resilience and sustainable profitability.

2. Concept and evolution of digital agriculture

Agriculture has undergone a series of technological and organizational transformations, moving from labour-intensive traditional production systems towards increasingly mechanized, information-intensive, automated and intelligent production environments. The transition commonly described as Agriculture 1.0 to Agriculture 5.0 should not be interpreted as a rigid chronological sequence because the boundaries between these stages differ across regions and agricultural systems. Rather, the framework provides a useful conceptual lens for understanding how technological capabilities have progressively changed the way agricultural resources, information and decisions are managed. Recent literature broadly characterizes Agriculture 1.0 by human and animal labour, Agriculture 2.0 by mechanization and intensive external inputs, Agriculture 3.0 by precision agriculture and location-specific management, Agriculture 4.0 by digital connectivity, IoT, big data and artificial intelligence, and Agriculture 5.0 by a more human-centred, sustainable and resilient integration of technology with agricultural systems.

2.1 Agriculture 1.0 to Agriculture 5.0

Agriculture 1.0 represents traditional agricultural systems in which production depended predominantly on human and animal labour, locally available resources and relatively simple implements. Productivity was strongly influenced by climatic conditions, soil fertility and accumulated indigenous knowledge. The transition to Agriculture 2.0 was associated with mechanization, improved irrigation, synthetic fertilizers, pesticides and high-yielding varieties, substantially increasing the capacity of agricultural systems to produce food while reducing dependence on manual labour. The subsequent emergence of Agriculture 3.0 introduced information-based management through technologies such as global positioning systems (GPS/GNSS), geographic information systems (GIS), remote sensing, yield monitoring and variable-rate application, thereby establishing the foundations of precision agriculture.

Agriculture 4.0 represents a further transition in which agricultural production becomes increasingly connected, automated and data-driven. Technologies associated with Industry 4.0—including the Internet of Things (IoT), cloud computing, big-data analytics, artificial intelligence, robotics, autonomous machinery and advanced sensing—enable continuous collection and processing of information from agricultural environments. Unlike earlier precision-agriculture approaches that primarily focused on spatial variability within fields, Agriculture 4.0 emphasizes interconnected systems in which data can move between sensors, machinery, farms, analytical platforms and

other actors in the agrifood system. Consequently, agricultural management can shift from periodic observation and reactive intervention towards continuous monitoring, prediction and increasingly automated decision-making.

Agriculture 5.0 extends this digital transformation by placing greater emphasis on the interaction among humans, intelligent machines and ecological systems. While Agriculture 4.0 is strongly associated with efficiency, connectivity, automation and data-driven optimization, Agriculture 5.0 incorporates broader objectives including sustainability, resilience, human-machine collaboration, ethical technology use and social inclusiveness. Thus, Agriculture 5.0 should not simply be regarded as Agriculture 4.0 with more advanced technologies; rather, it represents a shift towards determining how digital technologies can be deployed responsibly to achieve productivity together with environmental and societal objectives. Recent scholarship consequently describes Agriculture 5.0 as a human-centred and sustainability-oriented extension of the digital infrastructure developed under Agriculture 4.0.

2.2 Precision agriculture

Precision agriculture emerged as an important technological paradigm during the Agriculture 3.0 transition. It is fundamentally a management strategy based on observing, measuring and responding to spatial and temporal variability in agricultural production. GPS/GNSS, GIS, remote sensing, yield monitors, soil sensors and variable-rate technologies enable farmers to identify differences in crop, soil and environmental conditions and adjust inputs accordingly. The central objective is to apply the appropriate input, at the appropriate location and time, and in an appropriate quantity, thereby improving input-use efficiency and reducing unnecessary expenditure and environmental losses. Precision agriculture therefore established an important conceptual foundation for subsequent digital agriculture by transforming agricultural management from uniform field-level treatment towards location-specific decision-making.

The development of UAVs, high-resolution satellite imagery, IoT sensors and machine-learning algorithms has further expanded the capabilities of precision agriculture. Modern precision systems can integrate multiple data sources to generate detailed information on crop health, nutrient status, water stress, pest and disease occurrence and yield variability. Consequently, precision agriculture is increasingly becoming an important component of broader digital farming systems rather than an isolated technological approach.

2.3 Smart farming

Smart farming extends the concept of precision agriculture by emphasizing connectivity, automation, real-time monitoring and intelligent decision-making. Smart farming systems commonly integrate IoT sensors, wireless communication, cloud or edge computing, artificial intelligence, robotics, autonomous machinery and digital decision-support systems. The objective is not only to identify variability but also to continuously monitor agricultural systems and use computational intelligence to predict conditions and support or automate management responses.

The distinction between precision agriculture and smart farming is therefore primarily one of scope and technological integration. Precision agriculture concentrates strongly on spatial and temporal variability and site-specific management, whereas smart farming incorporates these principles into a more interconnected and automated

production environment. For example, a precision system may generate a map showing variation in crop nitrogen status, whereas a smart farming system may integrate sensor observations, AI-based analysis and automated machinery to determine and execute a variable-rate nitrogen application. This transition from measurement to intelligence and ultimately to action represents a major characteristic of contemporary digital agriculture.

2.4 Digital agriculture

Digital agriculture represents a broader concept encompassing the application of digital technologies across agricultural production and the wider agrifood value chain. It includes precision agriculture and smart farming but extends beyond the farm gate to encompass data platforms, digital advisory services, financial technologies, traceability systems, logistics, markets and other digitally enabled components of the food system. Klerkx *et al.* (2019) [2] emphasized that digital agriculture, smart farming and Agriculture 4.0 involve not only technological transformation but also changes in agricultural organizations, knowledge systems, business models and relationships among actors.

Accordingly, digital agriculture can be viewed as an ecosystem rather than a single technology. Field sensors, satellites, UAVs, farm machinery, mobile applications, cloud platforms and AI systems generate and process agricultural information, while farmers, agribusinesses, input suppliers, processors, financial institutions, insurers, retailers and policymakers can use the resulting information for decision-making. This broader perspective is particularly relevant to agribusiness management because the value of agricultural data increases when information generated at the production level can be connected with downstream activities such as procurement, storage, logistics, processing, marketing and risk management. Recent literature similarly emphasizes the evolution of digital agriculture towards an integrated technological ecosystem involving IoT sensing, big-data analytics, AI-based decision-making and digital traceability.

2.5 Agriculture 4.0

Agriculture 4.0 is closely associated with the application of Industry 4.0 principles to agriculture. It is characterized by interconnected devices, real-time data acquisition, cloud-based computing, artificial intelligence, autonomous machinery, robotics and advanced analytics. In this environment, agricultural operations increasingly become part of interconnected cyber-physical systems in which physical processes are monitored through sensors and interpreted through computational models.

The significance of Agriculture 4.0 lies in its ability to move agricultural management from a predominantly experience-based model towards a data-driven and predictive model. Historical production records can be combined with real-time weather, soil, crop and market information to improve forecasting and planning. AI can identify patterns within complex datasets, while UAVs and remote sensing can provide high-resolution information on field conditions. Such integration creates opportunities for earlier intervention, optimized resource allocation and improved operational efficiency. However, Agriculture 4.0 also introduces challenges concerning data ownership, interoperability, cybersecurity, technological costs, digital skills and unequal access to infrastructure. These issues are particularly important when evaluating whether technological advances translate into commercially viable and inclusive agribusiness systems.

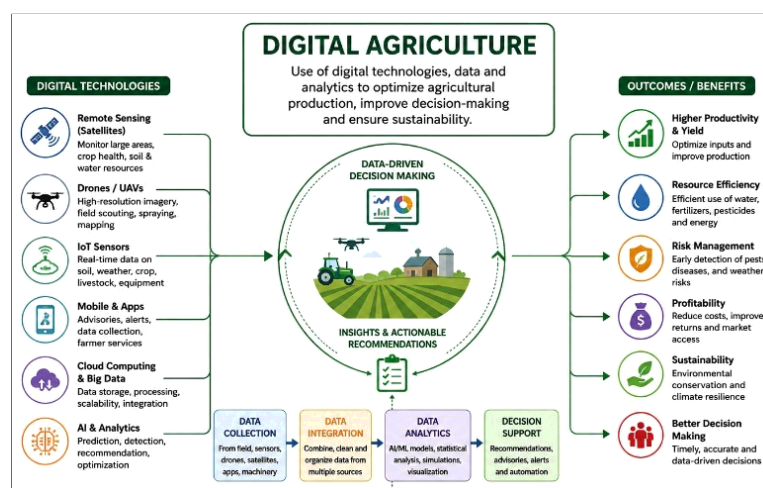


Figure 1. Conceptual Framework of Digital Agriculture: Integration of Digital Technologies, Data Analytics and Data-Driven Decision-Making for Sustainable Agribusiness Management

2.6 Data-driven agribusiness

The progression towards digital agriculture ultimately changes the role of data within agribusiness management. Traditionally, agricultural decisions have relied heavily on farmer experience, periodic field observations, historical records and relatively limited market information. Data-driven agribusiness introduces a more integrated approach in which information from farms, UAVs, satellites, IoT devices, weather stations, machinery, markets and supply chains can be combined and analysed to support managerial decisions. In this context, data become an economic and strategic resource rather than simply a by-product of agricultural operations.

Data-driven agribusiness can support production forecasting, input procurement, inventory management, financial planning, risk assessment, crop insurance, logistics, quality management, market forecasting and traceability. For example, UAV-derived crop information can improve estimates of expected production; AI models can convert these observations into yield forecasts; and agribusiness managers can subsequently use those forecasts for procurement, storage, transportation and marketing decisions. Similarly, combining field-level information with weather and market data can improve risk assessment and production planning. Thus, the ultimate significance of digital agriculture lies not merely in collecting more agricultural data but in transforming those data into actionable intelligence and economically valuable decisions.

The evolution from Agriculture 1.0 to Agriculture 5.0 can therefore be understood as a progression from labour → mechanization → precision → connectivity → intelligence and human-machine collaboration. Precision agriculture introduced location-specific management, smart farming added connectivity and automation, digital agriculture expanded digitalization across the agrifood system, and Agriculture 4.0 integrated these capabilities through data-centric technologies. Agriculture 5.0 builds upon this technological foundation while emphasizing sustainability, resilience, inclusiveness and human-machine-nature collaboration. For the present review, this evolutionary framework is particularly important because AI and drone technology sit at the intersection of sensing, intelligence and decision-making, providing a technological pathway through which digital agricultural data can be converted into improved agribusiness performance.

3. Artificial intelligence in agriculture

Artificial intelligence (AI) has emerged as one of the most influential technologies in the transition from conventional and precision agriculture towards intelligent, autonomous and data-driven agricultural

systems. Agricultural production generates large volumes of heterogeneous information from weather stations, soil sensors, satellite platforms, unmanned aerial vehicles (UAVs), farm machinery, crop-monitoring systems and market databases. AI provides computational methods for transforming these data into predictions, classifications, recommendations and automated decisions. In contrast to conventional statistical approaches that often depend on predefined relationships, AI-based methods can identify complex, nonlinear and high-dimensional relationships among environmental, agronomic and management variables. Consequently, AI is increasingly being applied to crop-yield forecasting, disease and pest diagnosis, crop monitoring, resource optimization, phenotyping, quality assessment and agricultural decision support. Recent reviews indicate that machine learning (ML), deep learning (DL), computer vision and emerging large-model technologies are becoming important components of digital agriculture, particularly when integrated with remote sensing, IoT and UAV-derived information.

3.1 Machine learning

Machine learning refers to computational approaches through which algorithms learn patterns and relationships from data and subsequently use the learned information to make predictions or classifications. In agriculture, ML has particular value because crop performance is influenced simultaneously by soil properties, temperature, rainfall, humidity, genotype, management practices, pest and disease pressure and other environmental variables. Algorithms such as linear regression, decision trees, random forests, support vector machines, artificial neural networks, gradient-boosting methods and other ensemble techniques have consequently been employed to analyse agricultural datasets and generate predictive models. Recent systematic evidence on crop-yield prediction shows extensive use of temperature, soil characteristics and vegetation-related variables, with Random Forest, linear regression and gradient-boosting methods among commonly used approaches.

Yield prediction is one of the most important applications of ML because reliable estimates of production can improve both farm-level and agribusiness-level planning. Yield models can combine historical yield records with weather variables, soil characteristics, crop-management information and remotely sensed vegetation indices to estimate expected production before harvest. Such forecasts can support decisions related to input procurement, labour planning, storage capacity, transportation, contract arrangements, pricing and marketing. Recent systematic reviews demonstrate increasing integration of ML and remote sensing for yield estimation, including the use of UAV-derived imagery and multisource environmental data.

Table. Case studies demonstrating applications of artificial intelligence in agriculture

No.	Agricultural application	Crop / system	AI technique / model	Major objective / outcome	Reference
1	Yield prediction	Multiple crops	Machine learning	Prediction of crop yield using environmental and management variables	Elavarasan & Durairaj Vincent (2021), <i>Sensors</i> . DOI: 10.3390/s21082689
2	Crop-yield prediction	Multiple crops	Deep learning	Review and application of DL models for yield forecasting	Oikonomidis <i>et al.</i> (2022). DOI: 10.1080/01140671.2022.2032213 (Royal Society of New Zealand Te Apārangi)
3	Rice yield prediction	Rice	ML/DL	Prediction of rice yield from agricultural and environmental data	De Clercq & Mahdi (2024). DOI: 10.1016/j.compag.2024.109852
4	Disease detection	Multiple crops	ML	Automated identification of crop diseases from sensor/image data	Benos <i>et al.</i> (2021), <i>Sensors</i> . DOI: 10.3390/s21082730
5	Plant disease recognition	Multiple crops	CNN / DL	Automated classification of disease symptoms	Ghimire <i>et al.</i> (2026). DOI: 10.5423/PPJ.RW.01.2026.0004 (PubMed)
6	Rice disease detection	Rice	Deep learning	Image-based recognition of rice diseases	Ferentinos (2018), <i>Computers and Electronics in Agriculture</i> , 145, 311–318. DOI: 10.1016/j.compag.2018.01.009
7	Tomato disease detection	Tomato	CNN	Classification of tomato leaf diseases	Fuentes <i>et al.</i> (2017), <i>Computers and Electronics in Agriculture</i> , 140, 115–126. DOI: 10.1016/j.compag.2017.05.027
8	Pest forecasting	Rice	ML + satellite + weather data	Prediction of pest population occurrence	Sakurai <i>et al.</i> (2019), <i>Applied Sciences</i> , 9, 4846. DOI: 10.3390/app9224846 (MDPI)
9	Pest forecasting	Multiple crops	Explainable DL	Forecasting pest outbreaks using meteorological time series	Wang & Zhang (2024), <i>Expert Systems with Applications</i> , 252, 124137. DOI: 10.1016/j.eswa.2024.124137 (ScienceDirect)
10	Rice pest prediction	Rice	Gradient Boosting + CNN	Early prediction of yellow stem borer, brown planthopper and green leafhopper	2026. DOI: 10.1016/j.procs.2026.06.608 (ScienceDirect)
11	Weed classification	Crops/weeds	ML/DL	Automated crop–weed classification for precision weed management	Ait El Caid <i>et al.</i> (2024). DOI: 10.1016/j.aiaa.2024.06.005 (ScienceDirect)
12	Weed detection	Agricultural fields	Deep learning	Detection and localization of weeds for site-specific control	Bahga Abdul-Hakeem <i>et al.</i> (2026). DOI: 10.1007/s42452-026-09205-9 (Springer)
13	Fruit detection	Orchard crops	Deep learning	Detection and counting of fruits for yield estimation	Koirala <i>et al.</i> (2019), <i>Computers and Electronics in Agriculture</i> , 162, 219–234. DOI: 10.1016/j.compag.2019.04.017 (ScienceDirect)
14	Fruit yield estimation	Orchard crops	CNN / object detection	Automated fruit detection and yield estimation	Koirala <i>et al.</i> (2019). DOI: 10.1016/j.compag.2019.04.017 (ScienceDirect)
15	Crop stress detection	Field crops	Deep learning	Identification of plant stress using image-based methods	Benos <i>et al.</i> (2021), <i>Sensors</i> . DOI: 10.3390/s21082730
16	Plant phenotyping	Crop plants	Computer vision / DL	Automated measurement of plant morphological traits	Uzal <i>et al.</i> (2024), <i>iScience</i> . DOI: 10.1016/j.isci.2023.108709

(continued on next page)

No.	Agricultural application	Crop / system	AI technique / model	Major objective / outcome	Reference
17	Crop monitoring	Precision agriculture	Computer vision	Automated monitoring of crop growth and health	<i>Artificial Intelligence in Agriculture</i> (2024). DOI: 10.1016/j.aiaa.2024.06.004 (EnviroClimate Journal)
18	UAV image analysis	Field crops	ML/DL	AI analysis of UAV imagery for precision agriculture	Preethi <i>et al.</i> (2026). DOI: 10.3233/APC210152 (Sage Journals)
19	UAV + disease detection	Field crops	CNN / computer vision	Disease identification from aerial imagery	Wang <i>et al.</i> (2024), <i>European Journal of Agronomy</i> . DOI: 10.1016/j.eja.2024.127477
20	UAV + yield estimation	Field crops	DL	Crop yield estimation using aerial imagery	Wang <i>et al.</i> (2024), <i>European Journal of Agronomy</i> . DOI: 10.1016/j.eja.2024.127477
21	Precision irrigation	Crops	ML	Prediction of irrigation requirements and water management	Benos <i>et al.</i> (2021), <i>Sensors</i> . DOI: 10.3390/s21082730
22	Soil fertility prediction	Agricultural soils	ML	Estimation and mapping of soil fertility properties	Li <i>et al.</i> (2020), <i>Geoderma</i> . DOI: 10.1016/j.geoderma.2020.114528
23	Soil property mapping	Agricultural soils	Random Forest / ML	Spatial prediction of soil properties	Wadoux <i>et al.</i> (2020), <i>Geoderma</i> . DOI: 10.1016/j.geoderma.2019.114100
24	Crop quality assessment	Agricultural products	ML/DL + imaging	Automated assessment of agricultural product quality	Deep-learning-based agricultural product assessment literature; review summarized in <i>Biosystems Engineering</i> (2024). DOI: 10.1016/j.biosystemseng.2024.07.002
25	Grain quality assessment	Food grains	Machine learning	Classification and quality evaluation using image/spectral characteristics	ML/DL quality-assessment studies summarized in recent review literature. (DOI)
26	Weather-based crop management	Crops	ML	Prediction of weather-related agricultural conditions	ML-based agricultural forecasting literature
27	Drought early warning	Crops	AI/ML	Early identification and prediction of agricultural drought	AI-enabled early-warning research, <i>Smart Agricultural Technology</i> (2026), DOI: 10.1016/j.atech.2026.101968 (ScienceDirect)
28	Plant-protection intelligence	Indian agriculture	Deep learning	Identification and spatial profiling of disease/pest hotspots using farmer helpline data	AgriIntel (2023), <i>Engineering Applications of Artificial Intelligence</i> , 117, 105555. DOI: 10.1016/j.engappai.2022.105555 (ScienceDirect)
29	Generative AI for agriculture	Agrifood systems	Generative AI / LLM	Farmer advisory, knowledge systems, precision farming and supply-chain applications	Pallottino <i>et al.</i> (2025), <i>Computers and Electronics in Agriculture</i> . DOI: 10.1016/j.compag.2025.109919
30	AI-enabled integrated pest management	Agricultural crops	ML + DL + robotics	Integration of pest detection, prediction and precision control	<i>Integrated Pest Management in the AI era</i> (2026), <i>Smart Agricultural Technology</i> . DOI: 10.1016/j.atech.2026.102397 (ScienceDirect)

Disease detection represents another important application of ML. Conventional disease diagnosis frequently depends on visual inspection by farmers or specialists and may be affected by subjectivity, limited expertise and delayed detection. ML models can analyse visual, spectral and environmental information to identify disease-associated patterns and classify affected plants. Early identification creates opportunities for targeted intervention, potentially reducing unnecessary pesticide applications and limiting yield losses. Recent reviews have documented the use of ML and DL algorithms for image-based diagnosis across several crops and emphasize the importance of image quality, representative datasets and field-level validation for reliable deployment.

ML can also support pest forecasting by combining historical pest observations with temperature, humidity, rainfall, crop stage and other environmental variables. Rather than responding only after pest populations reach economically damaging levels, predictive models can provide an indication of likely pest occurrence or outbreak risk. Such systems can contribute to integrated pest management by improving the timing and spatial targeting of interventions. Similarly, ML can

support weather and microclimate prediction, where relationships among historical weather observations, atmospheric variables and local field conditions are used to estimate temperature, rainfall, humidity or other variables relevant to agricultural decision-making. These predictions can subsequently inform irrigation scheduling, disease-risk assessment, crop-protection operations and harvest planning. The importance of ML therefore extends beyond prediction itself. Its principal contribution to digital agriculture is the conversion of complex agricultural observations into decision-relevant information. However, model performance depends strongly on the quality, quantity and representativeness of training data. Models developed under one crop, region, season or management system may not necessarily generalize to another environment. Problems associated with data scarcity, overfitting, model transferability and inconsistent evaluation procedures remain important barriers to practical deployment. Recent research on rice-yield forecasting, for example, highlights limited data availability, overfitting and regional generalization as continuing challenges.

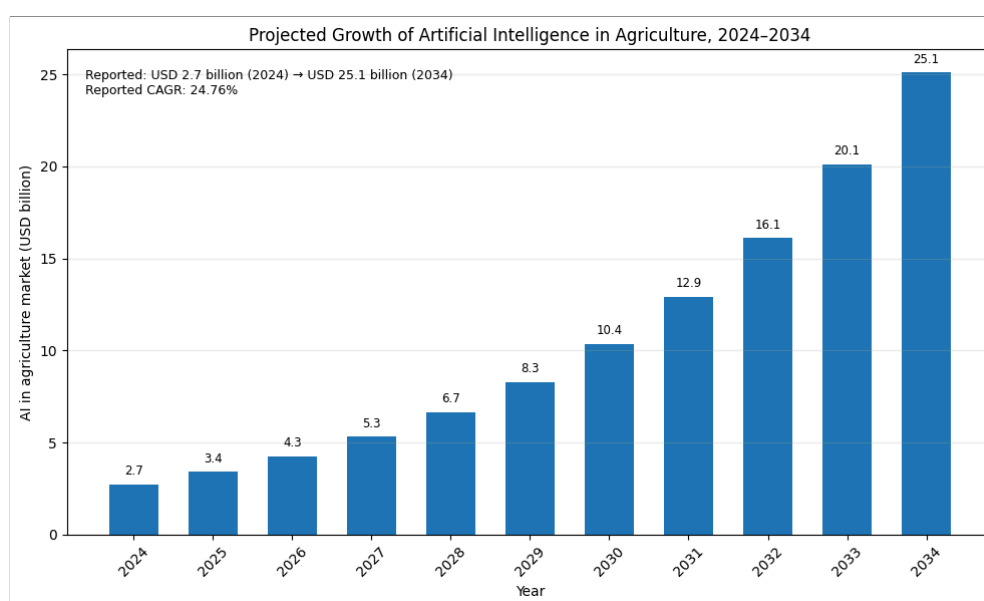


Figure 4. Growth of Artificial Intelligence in Agriculture, 2024–2034

3.2 Deep learning

Deep learning represents a subset of machine learning based primarily on multilayer neural-network architectures capable of learning increasingly complex representations directly from large datasets. Unlike many conventional ML workflows that require substantial manual feature engineering, deep-learning models can learn relevant features from raw or minimally processed images, time-series data and other high-dimensional inputs. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks and, more recently, transformer-based architectures have been applied to a wide range of agricultural problems. The increasing availability of high-resolution imagery from satellites and UAVs has further accelerated the use of DL in agricultural monitoring.

Image classification is one of the most established applications of DL in agriculture. CNN-based models can learn visual characteristics associated with crops, plant organs, disease symptoms, weeds, fruits and other agricultural objects. These systems can classify images according to crop species, health status, disease category, growth stage or other predefined classes. More advanced architectures, including transformer-based models, are increasingly being investigated because of their ability to model complex spatial relationships and contextual information in agricultural imagery.

Crop disease recognition has received particularly strong attention because disease symptoms are often visually detectable before severe yield losses occur. Deep-learning systems can learn colour, texture, shape and spatial characteristics associated with disease symptoms and subsequently classify images into healthy and diseased categories or identify specific disease types. Such approaches have demonstrated considerable potential for automated disease diagnosis, although performance obtained under controlled imaging conditions may not always translate directly to complex field environments containing variable illumination, occlusion, mixed symptoms and different crop growth stages. Recent reviews emphasize that field validation, robust datasets and model interpretability remain essential for practical deployment.

Weed identification is another major application of DL because accurate spatial identification of weeds can enable site-specific weed management. CNN-based object detection and segmentation models can distinguish weeds from crops and generate spatial information that can subsequently be used for precision herbicide application or mechanical weeding. The development of lightweight detection architectures, attention mechanisms and segmentation approaches has improved the possibility of deploying such systems on agricultural machinery and autonomous platforms. Nevertheless, crop-weed similarity, variation in weed morphology, changing illumination and differences among fields and seasons remain major challenges.

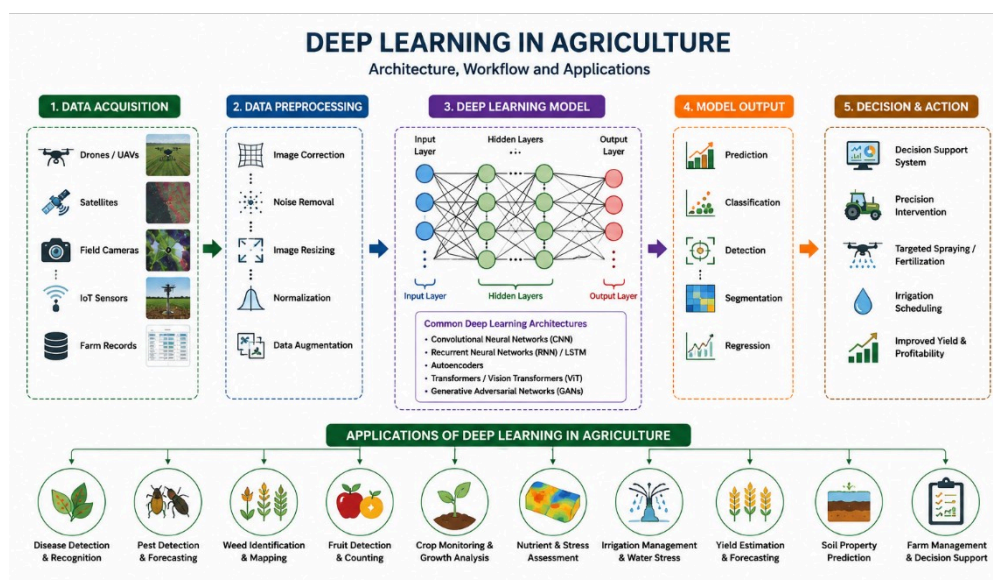


Figure 2. Deep Learning in Agriculture: Architecture, Workflow and Applications.

Fruit detection involves identifying and counting fruits, estimating their size and maturity, and locating them within a crop canopy. Deep-learning object-detection models can automate tasks that would otherwise require intensive manual labour. Fruit detection can contribute to yield estimation, harvest scheduling, robotic harvesting and postharvest planning. When combined with UAV or ground-based imagery, these systems can potentially provide information on spatial patterns of fruit distribution across orchards and facilitate more efficient resource allocation. More broadly, DL-based image analysis is increasingly being connected with agricultural automation and quality-management systems.

3.3 Computer vision

Computer vision is a major interface between AI and agricultural sensing because it enables machines to interpret visual information obtained from cameras and other imaging sensors. Agricultural computer-vision systems generally involve a sequence of image acquisition, preprocessing, segmentation or object detection, feature extraction or representation learning, classification and decision-making. The combination of computer vision with ML and DL has substantially expanded the ability to automatically quantify crop and plant characteristics that were traditionally measured manually. Recent reviews describe computer vision as a key component of smart agriculture and precision farming, with applications extending from crop monitoring and disease detection to plant phenotyping and product-quality assessment.

Crop monitoring is among the most direct applications of computer vision. Images acquired from ground platforms, agricultural machinery, satellites or UAVs can be analysed to identify changes in canopy development, plant density, growth stage, crop stress and disease symptoms. Integration with multispectral or thermal imagery can provide information beyond visible appearance, allowing computer-vision systems to detect physiological changes associated with water stress, nutrient deficiency or other forms of crop stress. The resulting information can support timely field interventions and improve spatial targeting of agricultural inputs.

Plant phenotyping is another important domain in which computer vision has transformed agricultural research and production. Automated imaging can quantify plant height, leaf area, canopy architecture, biomass-related traits, growth rates and other morphological or physiological characteristics at high throughput. This is particularly valuable for crop breeding because large numbers of genotypes can be evaluated objectively and repeatedly. Modern computer-vision-based phenotyping systems increasingly combine RGB, depth, multispectral and hyperspectral information with ML and DL algorithms. Recent comprehensive reviews identify automated image acquisition,

segmentation, feature extraction and classification as important components of high-throughput plant phenotyping.

Quality assessment represents an important extension of computer vision from primary production to postharvest and agribusiness management. Imaging systems can be used to assess external appearance, size, colour, maturity, defects and other quality attributes of fruits and agricultural products. When combined with hyperspectral, near-infrared or other non-destructive sensing technologies, AI-based systems can also estimate internal quality characteristics that cannot be reliably determined through conventional visual inspection. These technologies can facilitate automated grading, sorting, quality control and traceability while reducing dependence on subjective manual assessment. Recent research highlights the growing integration of AI with non-destructive sensing for rapid and high-throughput agricultural product-quality assessment.

The importance of computer vision for the present review is particularly significant because it forms a technological bridge between drone-based data acquisition and AI-based decision-making. UAVs can acquire high-resolution images of agricultural fields, while computer-vision algorithms transform those images into meaningful information such as crop health maps, disease distribution, weed locations, plant counts and yield-related indicators. Thus, computer vision provides the analytical layer through which drone observations can become actionable information for precision management and agribusiness planning.

3.4 Generative AI and agricultural decision support

The emergence of generative artificial intelligence (GenAI), large language models (LLMs), large vision models and multimodal AI is introducing a new dimension to digital agriculture. Conventional agricultural AI systems are generally designed for specific prediction or classification tasks, whereas generative AI can process and generate text, images, summaries, recommendations and other forms of information. This capability creates opportunities for developing more accessible agricultural decision-support systems in which farmers and agribusiness professionals can interact with complex datasets through natural-language interfaces. A recent comprehensive review of GenAI in agriculture identified potential applications across precision farming, pest and disease management, crop improvement, supply-chain optimization and broader agri-food systems, while also highlighting hallucination and reliability as important concerns.

Farmer advisory is one of the most promising applications. LLM-based systems can potentially provide farmers with conversational access to information concerning crop management, pest and disease identification, weather-related decisions, input use and other agricultural questions. Multilingual and multimodal systems may further allow farmers to interact using local languages, text, photographs or

voice. Recent reviews indicate that agricultural LLMs are being investigated for question answering, agricultural knowledge services and decision support, although domain-specific adaptation and reliable knowledge integration remain important requirements.

Automated reporting provides another potential application for agribusiness management. AI systems can combine information from field sensors, UAV surveys, weather databases and farm records to generate structured reports on crop condition, field operations, resource use and production status. This can reduce the time required to manually interpret and communicate large quantities of agricultural information. For agribusiness enterprises managing multiple farms or production units, automated reporting could facilitate standardized monitoring and faster managerial review.

Knowledge systems can be developed through the integration of LLMs with agricultural knowledge graphs, databases and validated information repositories. Knowledge graphs provide structured representations of relationships among crops, pests, diseases, chemicals, environmental conditions and management practices, while LLMs provide natural-language interaction and information-generation capabilities. Their combination could enable more structured agricultural knowledge services and reduce dependence on unverified free-form responses. Recent research specifically identifies the integration of knowledge graphs and LLMs as a promising direction for agricultural knowledge management and intelligent decision support.

Market intelligence represents an especially relevant application for agribusiness management. Generative AI can potentially synthesize information from market reports, price databases, weather forecasts, production estimates, consumer trends and other sources to support procurement, pricing, logistics and marketing decisions. Emerging research indicates that agricultural large-language-model systems are being explored not only for farm-level production management but also for analysing market dynamics and broader agricultural information.

However, the use of GenAI in agriculture requires considerably greater caution than simply deploying a general-purpose conversational system. Agricultural recommendations can have direct economic and environmental consequences; therefore, factual accuracy, traceability of information, domain adaptation and human oversight are essential. Generative systems may produce plausible but incorrect information, commonly described as hallucination, and may also reproduce biases present in their training data. Data privacy, cybersecurity, intellectual-property rights and unequal access to computational infrastructure are additional concerns. Recent reviews emphasize that responsible agricultural deployment requires reliable agricultural datasets, domain-specific validation, appropriate knowledge integration and mechanisms for human oversight.

Overall, AI in agriculture is progressing from prediction and classification towards integrated agricultural intelligence. Machine learning provides predictive analytics; deep learning enables high-dimensional image and pattern recognition; computer vision converts visual information into measurable agricultural traits; and generative AI increasingly provides natural-language interfaces and knowledge-based decision support. Their integration with IoT, remote sensing and UAV technologies creates a pathway from data acquisition → AI analysis → agricultural intelligence → decision support → management action. This progression is particularly important for agribusiness because AI-generated intelligence can potentially improve not only crop production but also resource allocation, risk management, operational planning, supply-chain coordination, quality management and market decisions.

For example, a UAV can capture high-resolution imagery of a crop field, after which a deep-learning model can identify disease symptoms and generate a spatial disease map. The resulting information can then be used to implement targeted spraying, reducing unnecessary pesticide application, labour and operational costs. Similarly,

4. Drone technology in agriculture

Unmanned aerial vehicles (UAVs), commonly known as agricultural drones, have become important tools in digital and precision agriculture because they can acquire high-resolution, timely and spatially explicit information from agricultural fields. Depending on their design and purpose, UAVs can be broadly classified into multirotor, fixed-wing and hybrid vertical take-off and landing (VTOL) platforms. Multirotor drones provide high manoeuvrability and are suitable for small fields and detailed crop monitoring, whereas fixed-wing UAVs can cover larger areas with longer flight endurance. Hybrid VTOL platforms combine vertical take-off and landing capabilities with relatively efficient forward flight, providing greater operational flexibility. UAV-based remote sensing is increasingly used to complement satellite and ground-based observations by providing flexible, high-resolution information at critical crop-growth stages.

The effectiveness of agricultural UAVs depends strongly on their on-board sensors. RGB cameras provide visible-spectrum imagery useful for crop stand assessment, plant counting, canopy monitoring, weed identification and visible disease symptoms. Multispectral sensors capture information from selected spectral bands, commonly including visible and near-infrared wavelengths, enabling vegetation-index-based assessment of crop vigour, biomass and stress. Hyperspectral sensors acquire information across numerous narrow spectral bands and can provide detailed information about plant physiological and biochemical characteristics, although they generally involve higher data-processing requirements and greater operational complexity. Thermal sensors measure canopy temperature and are particularly useful for detecting water stress and assessing irrigation requirements. LiDAR provides three-dimensional information on crop structure, canopy height and field topography. The combination of different sensors can therefore provide complementary information for comprehensive crop assessment.

UAVs have diverse applications across agricultural production. Crop health monitoring uses aerial imagery and vegetation indices to identify spatial variation in crop growth and stress. Nutrient assessment can help identify nutrient-related variability and support site-specific fertilization. Thermal and multispectral observations can assist irrigation management by identifying areas experiencing water stress. UAV imagery can also support pest and disease detection, weed mapping and crop stand assessment through high-resolution spatial observations. Furthermore, UAV-derived information can contribute to yield estimation, particularly when combined with crop-growth indicators, plant counts and machine-learning models. UAVs are also increasingly being explored for targeted spraying, enabling localized application of pesticides, fertilizers or biological agents. High-resolution aerial imagery additionally supports field mapping, boundary delineation, crop-zone identification and generation of digital surface and terrain information. Collectively, these applications demonstrate that UAVs function not merely as aerial imaging platforms but as important data-acquisition components of modern digital agriculture.

5. Integration of AI and drone technology

The integration of AI and UAV technology creates a more powerful digital-agriculture system than either technology can provide independently. UAVs serve primarily as **data-acquisition platforms**, capturing high-resolution RGB, multispectral, hyperspectral, thermal or LiDAR information, whereas AI provides the computational capability to process these large and complex datasets and convert them into meaningful agricultural intelligence. The integrated workflow can be represented as:

Drone → Image/Data Acquisition → Image Processing → AI Analysis → Prediction/Classification → Decision Support → Farm/Agribusiness Action

UAV imagery combined with AI can identify crop-water stress, generate irrigation-priority zones and support precision irrigation. In yield management, drone imagery can be analysed using machine-learning models to estimate expected production, which can subsequently as

sist agribusiness managers in harvest planning, storage, transportation, procurement and marketing decisions.

Thus, AI-drone integration represents a transition from data collection to data-driven action. Its major value for agribusiness lies in converting field-level observations into actionable information that can improve resource-use efficiency, reduce production risks, optimize operational costs and ultimately contribute to improved productivity, profitability and sustainability. Recent research identifies the combination of UAV remote sensing and AI/deep learning as an important direction for precision agriculture, particularly for automated crop monitoring, disease detection, weed identification and yield estimation (Wang *et al.*, 2024; Makam *et al.*, 2024) [8, 11].

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Conclusion

Digital agriculture represents a fundamental transformation in the way agricultural information is generated, analysed and converted into management decisions. The progression from conventional agriculture through precision and smart farming towards Agriculture 4.0 and Agriculture 5.0 demonstrates a gradual shift from labour- and ex-

perience-based management to connected, automated, intelligent and increasingly data-driven agricultural systems. Within this transformation, artificial intelligence and drone technology occupy complementary positions: UAVs provide flexible and high-resolution data acquisition, while AI provides the analytical intelligence required to interpret complex agricultural information and generate predictions, classifications and recommendations. The review demonstrates that machine learning, deep learning and computer vision have expanded the potential for automated crop monitoring, yield prediction, disease and pest recognition, weed mapping, plant phenotyping, fruit detection, nutrient and water-stress assessment and agricultural forecasting. Similarly, UAV platforms equipped with RGB, multispectral, hyperspectral, thermal and LiDAR sensors can provide detailed spatial information that is difficult to obtain through conventional field observations. The greatest value emerges when these technologies are integrated rather than used independently. The pathway drone-based data acquisition → AI processing → prediction → decision support → precision intervention can convert raw agricultural observations into actionable intelligence for both farm-level and agribusiness-level decision-making.

From an agribusiness perspective, the implications extend beyond improved crop production. AI- and drone-enabled systems can contribute to input optimization, production planning, labour management, crop-risk assessment, yield forecasting, harvest scheduling, storage and logistics planning, quality management, supply-chain coordination, market intelligence and profitability improvement. Consequently, digital agriculture should increasingly be viewed as an agribusiness intelligence ecosystem, rather than simply a collection of precision-farming technologies. Despite these opportunities, techno-

logical advancement alone will not guarantee successful adoption. High investment costs, inadequate connectivity, limited digital literacy, fragmented agricultural holdings, data-quality problems, interoperability constraints, cybersecurity risks, regulatory requirements and uncertainties surrounding AI explainability remain important barriers. The challenge is particularly significant for small and marginal farmers, for whom ownership of sophisticated equipment may not be economically feasible. Therefore, service-based approaches such as drone-as-a-service, AI-as-a-service, custom hiring centres, cooperative models and farmer-producer-organization-based digital services may provide more inclusive pathways for technology adoption.

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