



Digital Agriculture and Artificial Intelligence for Smart Crop Management: Advances, Applications and Future Prospects

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Agriculture is undergoing a rapid technological transformation due to increasing pressure on natural resources, climate variability, rising production costs, labour shortages and the growing demand for food. Digital agriculture integrates information and communication technologies, remote sensing, Internet of Things (IoT), sensors, unmanned aerial vehicles, geographic information systems, cloud computing, big-data analytics and artificial intelligence (AI) to improve the efficiency and sustainability of agricultural production. Among these technologies, AI and machine learning (ML) have emerged as important tools for converting large and complex agricultural datasets into useful information for crop management decisions. AI-based approaches are increasingly being applied to crop monitoring, disease and pest detection, weed identification, soil fertility assessment, irrigation scheduling, nutrient management, yield prediction and harvest planning. Remote sensing combined with ML provides opportunities for spatially explicit assessment of crop growth, soil and water conditions, particularly at large scales. The integration of AI with IoT, satellite imagery, drones and farm sensors can facilitate near-real-time decision-making and the development of intelligent crop management systems. However, high initial investment, limited digital infrastructure, data quality, interoperability, farmer digital literacy, algorithm transparency, data ownership and the digital divide remain important barriers to widespread adoption. Future progress will depend on affordable, farmer-oriented, explainable and locally adapted AI solutions supported by reliable data and appropriate institutional frameworks. This review discusses the major components, applications, benefits, limitations and future prospects of digital agriculture and AI for smart and sustainable crop management.

Keywords: Artificial intelligence, digital agriculture, machine learning, precision agriculture, remote sensing, crop management, Internet of Things

Introduction

Agriculture is increasingly required to produce more food while using land, water, nutrients and energy more efficiently. At the same time, agricultural production is exposed to climate variability, extreme weather events, soil degradation, pest and disease outbreaks, labour shortages and increasing input costs. These challenges have stimulated the development of technologies capable of supporting timely, site-specific and evidence-based agricultural decisions. The transition from conventional agriculture to precision agriculture and subsequently to digital and smart agriculture has created new opportunities for improving crop production. Digital agriculture involves the collection, integration, processing and use of agricultural data to improve decisions across the production system. Modern digital agriculture

incorporates remote sensing, mobile technologies, IoT, sensors, cloud computing, artificial intelligence, machine learning, robotics, drones, geographic information systems and big-data analytics (Shamshiri *et al.*, 2024).

Artificial intelligence has become particularly important because agricultural systems generate large volumes of heterogeneous data from soil sensors, weather stations, satellites, drones, machinery, crop images and farmer records. AI and ML can identify relationships within these datasets and provide predictions or recommendations that are difficult to obtain through conventional approaches (Javaid *et al.*, 2024). Recent reviews have documented applications of AI in crop selection, yield prediction, soil compatibility assessment, water management, disease detection and resource optimization (Khan *et al.*, 2025).

In India, the integration of remote sensing and machine learning has received increasing attention for crop, soil and water management. Bhatia *et al.* (2023) reported that machine learning combined with remote sensing has considerable potential for crop yield estimation, crop classification, disease prediction, water management, drought monitoring and soil management in Indian agriculture. Therefore, the integration of digital agriculture and AI represents an important pathway towards smart crop management, where agricultural operations can increasingly be based on real-time observations, predictive analytics and site-specific recommendations rather than uniform management practices.

Concept Of Digital Agriculture

Digital agriculture can be broadly described as the use of digital technologies, data and analytical systems to improve agricultural production, resource management and decision-making. It represents an evolution from conventional farming towards increasingly connected and information-driven agricultural systems (FAO, 2025).

The major components of digital agriculture include:

- Remote sensing and satellite imagery
- Unmanned aerial vehicles (UAVs) and drones
- Internet of Things (IoT)
- Soil and crop sensors
- Automatic weather stations
- Geographic Information Systems (GIS)
- Mobile applications
- Cloud computing
- Big-data analytics
- Artificial intelligence and machine learning
- Robotics and autonomous machinery
- Digital decision-support systems

Digital agriculture therefore does not represent a single technology. Instead, it is an interconnected technological ecosystem in which data are collected from agricultural fields, transmitted through communication networks, analysed using computational tools and converted into actionable recommendations (Shamshiri *et al.*, 2024). The Food and Agriculture Organization has emphasized that digital technologies and AI can contribute to transforming agrifood systems by improving information delivery, decision-making and resource management (FAO, 2025).

Artificial Intelligence in Agriculture

Artificial intelligence refers to computational approaches that enable machines to perform tasks requiring functions commonly associated with human intelligence, such as learning, pattern recognition, prediction and decision-making. Important AI approaches used in agriculture

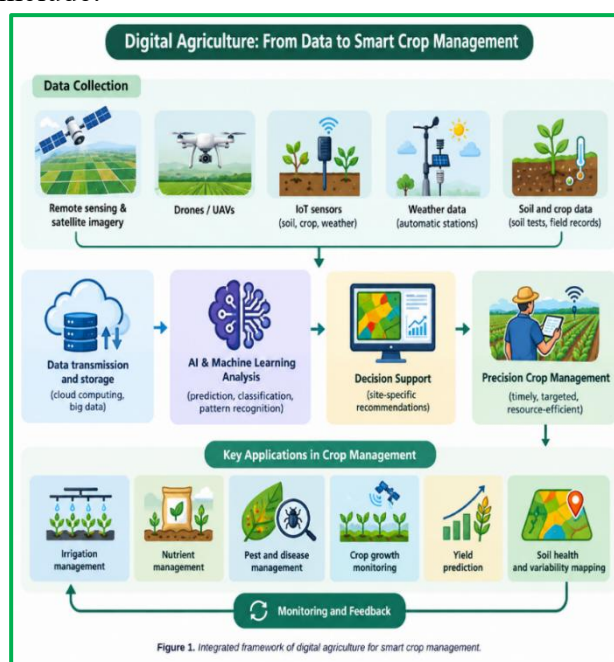


Figure 1. Integrated framework of digital agriculture for smart crop management.

include machine learning, deep learning, computer vision, predictive analytics and, increasingly, generative AI (Javaid *et al.*, 2024; Aijaz *et al.*, 2025).

Machine Learning

Machine learning (ML) enables computer systems to learn patterns from existing agricultural datasets and generate predictions or classifications without requiring explicit programming for every situation. In smart crop management, commonly used ML techniques include Random Forest, Support Vector Machine (SVM), Decision Tree, Gradient Boosting, K-Nearest Neighbour (KNN), Artificial Neural Networks (ANNs), and regression-based models. These algorithms can analyse large and complex datasets obtained from remote sensing, IoT sensors, weather observations, soil information and crop records. ML has been increasingly applied for crop classification, yield prediction, disease detection, soil and nutrient mapping, water management and agricultural risk assessment, thereby supporting timely and site-specific crop management decisions (Bhatia *et al.*, 2023; Wang *et al.*, 2024).

Deep Learning

Deep learning uses multi-layer neural networks to identify complex patterns from large datasets. Convolutional Neural Networks (CNNs) are particularly important for image-based agricultural applications. Deep-learning models are increasingly being used for crop disease detection, weed identification, crop classification, plant phenotyping and yield prediction (Khan *et al.*, 2025).

Computer Vision

Computer vision enables agricultural systems to interpret and analyse images acquired through smartphones, digital cameras, drones and satellite platforms. It has emerged as an important tool for automated crop monitoring and decision-making, with applications in disease identification, weed detection, fruit counting, crop stand assessment, plant phenotyping, crop maturity assessment and biomass estimation. By extracting visual features such as colour, shape, texture and canopy characteristics, computer vision models can provide rapid and non-destructive assessment of crop conditions. Recent reviews have highlighted the use of convolutional neural network (CNN)-based approaches for weed and disease detection, crop classification, water management and yield prediction, demonstrating their potential for improving the accuracy and efficiency of digital agriculture (El Sakka *et al.*, 2025).

Predictive Analytics

AI models can combine historical and real-time information to predict crop yield, pest outbreaks, water requirements and weather-related risks.

Crop-yield prediction is one of the most extensively studied applications of ML in agriculture. A systematic review by Shawon *et al.* (2025) demonstrated the growing use of machine-learning approaches for crop-yield prediction using combinations of environmental, crop and management variables.

Digital Technologies Supporting Smart Crop Management

Remote Sensing

Remote sensing provides information about agricultural fields without direct physical sampling. Satellite platforms can provide repeated observations over large areas, whereas drones can provide high-resolution information at field level.

Remote sensing can be used for:

- Crop identification
- Crop growth monitoring
- Vegetation assessment
- Drought monitoring
- Nutrient stress detection
- Soil moisture assessment
- Disease and pest monitoring
- Yield estimation

The combination of remote sensing and ML is particularly useful because AI algorithms can transform large volumes of spectral and spatial information into management-relevant information (Bhatia *et al.*, 2023; Wang *et al.*, 2024).

Internet of Things

IoT refers to interconnected devices capable of collecting and transmitting information. Agricultural IoT systems may include soil-moisture sensors, temperature sensors, humidity sensors, weather stations, nutrient sensors and crop-canopy sensors.

The data generated by these devices can be analysed using AI to produce real-time recommendations for irrigation, fertilization, pest management and other crop-management decisions (Muhammed *et al.*, 2024).

Drones and UAVs

UAVs provide high-resolution images and can be equipped with RGB, multispectral or thermal cameras. AI-based analysis of UAV imagery can identify spatial variation in crop growth, diseases, weeds, water stress and nutrient status. The integration of UAVs, remote sensing and deep learning is increasingly being explored for crop monitoring and plant-health assessment (El Sakka *et al.*, 2025).

Geographic Information Systems

Geographic Information Systems (GIS) enable agricultural information to be stored, analysed and visualized spatially. Integration of GIS with remote sensing and machine learning supports soil-fertility and yield mapping, crop suitability assessment, irrigation planning, disease-risk mapping, nutrient management and land-use planning. Thus, GIS-based digital tools help identify spatial variability and facilitate targeted and efficient crop-management decisions (Bhatia *et al.*, 2023; Wang *et al.*, 2024).

Applications Of Ai In Smart Crop Management

Crop Growth Monitoring

Traditional crop monitoring generally depends on field visits and visual assessment. Digital technologies enable continuous monitoring using sensors, satellites and drones.

AI can analyse vegetation indices, canopy characteristics, spectral information and environmental variables to identify spatial and temporal variation in crop growth (Shamshiri *et al.*, 2024). Such systems can help identify areas of poor crop establishment, nutrient deficiency, water stress or other abnormalities at an early stage.

Precision Irrigation Management

Water scarcity is a major constraint to sustainable agricultural production, while uniform irrigation may result in over- or under-application because crop water requirements vary across fields and growth stages. AI-based irrigation systems can integrate soil moisture, weather conditions, crop growth stage, evapotranspiration, temperature, humidity and rainfall forecasts to determine the appropriate timing and amount of irrigation. Integration of IoT sensors and AI therefore provides opportunities to improve irrigation scheduling and water-use efficiency (Shamshiri *et al.*, 2024).

Precision Nutrient Management

Uniform fertilizer application may lead to nutrient losses in some areas and insufficient supply in others. Digital technologies can identify spatial variation in soil properties and crop nutrient status using soil-test data, remote sensing, crop biomass and historical yield information. AI can integrate these datasets to develop site-specific nutrient recommendations, thereby improving nutrient-use efficiency, reducing input losses and minimizing environmental impacts. Recent advances in digital image processing and remote sensing further demonstrate the potential of digital technologies for crop nitrogen management (Konara *et al.*, 2024).

Disease Detection and Management

Early detection of crop diseases is essential for minimizing yield and economic losses. AI-based disease detection generally involves image acquisition, image processing, feature extraction and classification using machine-learning or deep-learning models. Images obtained from smartphones, drones and field cameras can be analysed to identify disease symptoms and plant-health problems. Future systems can combine disease identification with weather

conditions, crop growth stage and field history to predict disease development and support timely intervention (El Sakka *et al.*, 2025).

Weed Detection and Management

AI and computer vision can distinguish weeds from crop plants using characteristics such as shape, colour, texture, spectral response and spatial position. AI-enabled machinery can facilitate site-specific weed management by identifying weed-infested areas and targeting interventions only where required. This approach has the potential to reduce unnecessary herbicide application and improve weed-control efficiency. Recent studies have highlighted the increasing use of computer vision, deep learning and UAV imagery for real-time weed detection (Khan *et al.*, 2025; El Sakka *et al.*, 2025).

Crop Yield Prediction

Crop yield prediction is an important application of AI because it can integrate weather, soil properties, crop variety, sowing date, management practices, satellite imagery and historical yield data. Machine-learning models can identify complex and nonlinear relationships among these variables and provide yield estimates before harvest. Reliable yield prediction can support harvest planning, storage, marketing, crop insurance, food-security assessment and supply-chain management (Shawon *et al.*, 2025).

Soil Fertility and Soil Health Assessment

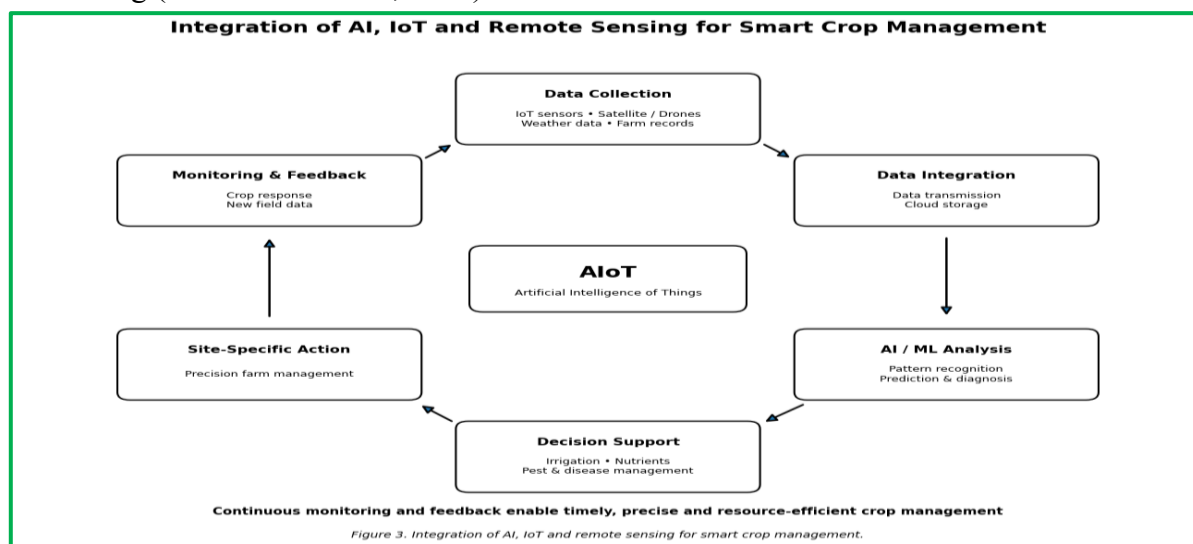
AI can assist in assessing spatial variability in soil fertility and soil health by integrating laboratory soil-test results with remote sensing and environmental datasets. Applications include soil-fertility mapping, soil organic carbon estimation, nutrient prediction, soil-moisture assessment, soil-degradation monitoring and management-zone delineation. The integration of AI with spatial information can help shift soil management from generalized recommendations towards more location-specific and resource-efficient practices (Wang *et al.*, 2025).

Crop Selection and Sowing Decisions

AI-based decision-support systems can analyse soil characteristics, climatic conditions, historical crop performance and other relevant information to support crop selection and sowing decisions. AI models can also assist in identifying suitable sowing windows by considering weather forecasts, soil moisture, temperature, historical climate patterns and crop requirements. Such predictive approaches can help farmers select suitable crops and optimize sowing time under variable climatic conditions.

Integration of AI, IoT and Remote Sensing

The greatest potential of digital agriculture lies not in individual technologies but in their integration. This integrated approach creates a feedback loop in which agricultural decisions can be continuously adjusted according to changing field conditions. The concept of Artificial Intelligence of Things (AIoT) combines IoT-based sensing with AI-based analysis. AIoT can support intelligent decision-making for irrigation, fertilization, pest management and crop monitoring (Muhammed *et al.*, 2024).



Role of Digital Agriculture in Climate-Smart Crop Management

Climate change increases uncertainty in crop production through changing temperature, rainfall patterns, droughts, floods and extreme weather events. AI can contribute to climate-smart agriculture through three major pathways.

Adaptation

- Weather-based crop advisories
- Drought-risk prediction
- Heat-stress assessment
- Irrigation optimization
- Climate-based crop planning

Mitigation

- Improved fertilizer-use efficiency
- Reduced fuel use through optimized field operations
- Better irrigation efficiency
- Precision application of agricultural inputs
- Improved soil-carbon management

Resilience

- Early-warning systems
- Crop-risk assessment
- Yield forecasting
- Pest and disease prediction
- Climate-informed decision support

The integration of AI, digital technologies and precision agriculture can therefore contribute to more efficient and resilient agricultural systems (FAO, 2025; Aijaz *et al.*, 2025).

Benefits of AI-Based Smart Crop Management

The major potential benefits are summarized below.

Application	AI-based opportunity	Expected benefit
Crop monitoring	Automated and repeated monitoring	Early identification of crop stress
Irrigation	Site- and time-specific irrigation	Improved water-use efficiency
Nutrient management	Variable-rate recommendations	Improved nutrient-use efficiency
Disease management	Image-based detection	Early intervention
Weed management	Targeted weed detection	Reduced unnecessary herbicide application
Yield prediction	Data-driven forecasting	Better harvest and market planning
Soil management	Digital soil mapping	Site-specific management
Weather management	Predictive analytics	Improved climate-risk management

The integration of digital technologies can therefore improve agricultural decision-making while supporting resource-use efficiency and sustainable production (Shamshiri *et al.*, 2024; Aijaz *et al.*, 2025).

Limitations And Challenges

Despite considerable technological progress, widespread adoption of AI in agriculture remains challenging.

High Initial Cost: Sensors, drones, high-performance computing systems and automated machinery may require substantial investment, which can limit adoption among small and marginal farmers (FAO, 2025).

Data Quality: AI models depend heavily on the quality, quantity and representativeness of training data. Poor-quality or biased datasets can produce unreliable recommendations (Wang *et al.*, 2024).

Digital Infrastructure: Reliable internet connectivity, electricity, cloud services and communication networks are essential for many digital-agriculture applications.

Digital Literacy: Farmers need appropriate training to interpret digital information and convert AI-generated recommendations into practical farm actions.

Interoperability: Agricultural data are often generated by different sensors, platforms and software systems. Lack of interoperability can make data integration difficult (Muhammed *et al.*, 2024).

Data Ownership and Privacy: Questions concerning who owns farm data, who can access it and how it can be used are becoming increasingly important as agriculture becomes more data-driven.

Explainability: Farmers may hesitate to follow recommendations from systems that provide a prediction without explaining why that recommendation was generated. Explainable AI is therefore important for building trust.

Digital Divide: The benefits of AI should not be limited to large commercial farms. Smallholders and resource-constrained farming communities must also be able to access and use appropriate technologies.

Future Prospects

The future of smart agriculture is expected to move towards increasingly integrated and autonomous systems.

Generative AI for Farmer Advisory

Generative AI may provide farmers with interactive advisory services using text, voice, images and other information formats. The development of digital agriculture and AI is increasingly moving towards integrated innovation ecosystems that connect agricultural problems, data, AI tools and field deployment (FAO, 2025).

Explainable AI

Future agricultural AI systems should not only provide predictions but also explain the major factors responsible for those predictions.

Edge AI

Processing information directly on smartphones, sensors, drones or farm machinery can reduce dependence on continuous internet connectivity.

AI-Based Autonomous Machinery

AI can support autonomous navigation, precision spraying, mechanical weeding and harvesting. Machine-learning and computer-vision systems are increasingly being investigated for agricultural automation (El Sakka *et al.*, 2025).

Digital Twins

Digital twins can create virtual representations of agricultural fields and simulate different management scenarios before actual implementation. AIoT research has identified digital twins as an emerging technology with potential applications in smart agriculture (Muhammed *et al.*, 2024).

Farmer-Centred Digital Agriculture

The future success of AI will depend not only on technological sophistication but also on affordability, simplicity, reliability and usefulness to farmers.

Conclusion

Digital agriculture and AI are transforming crop management through data-driven, site-specific and predictive decision-making. The integration of remote sensing, IoT, drones, GIS and AI support crop monitoring, precision irrigation, nutrient management, disease detection and yield prediction. However, high costs, limited infrastructure, digital skill gaps and data-related concerns remain important challenges. Future digital agriculture should be farmer-centred,

affordable, inclusive and locally adaptable to improve productivity, resource-use efficiency, climate resilience and sustainable food security.

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