Discover Agriculture

Review

Applications of AI in precision agriculture

Garima Gupta[1] · **Sudhir Kumar Pal**[1]

Received: 13 November 2024 / Accepted: 15 April 2025
Published online: 25 April 2025
© The Author(s) 2025 OPEN

Abstract
Precision agriculture (PA) leverages advanced technologies to optimize field-level management regarding crop farming. By using data analytics, satellite imagery, and various sensors, PA aims to increase crop yields while minimizing environmental impact. Artificial intelligence (AI) plays a crucial role in enhancing these capabilities, enabling more accurate predictions of soil, disease, pests and weeds, efficient resource management, and better decision-making processes. This review explores the diverse applications of AI in precision agriculture, highlighting the benefits and challenges associated with these advancements. It elaborates on various AI based tools and software which can help farmers customize their farming practices. It also throws light on the various challenges currently existing which inhibit the implementation of these latest technologies. The major challenge of data collection, data ownership and data privacy along with the huge cost of implementing the AI based setup are discussed. The review also focuses on the future AI technologies in agriculture like climate prediction, precision livestock farming, vertical agriculture etc.

Keywords Precision agriculture · Artificial intelligence · Crop management · Predictive analytics · Irrigation · Pest control · Farm automation · Machine learning · Computer vision · IoT

1 Introduction

Agricultural activities are fundamental to livelihoods, boosting GDP, supporting national trade, reducing unemployment, supplying raw materials for other industries, and driving overall economic development. As the global population continues to grow rapidly, it is essential to reassess agricultural practices and explore innovative solutions to sustain and enhance them. The integration of AI into agriculture will be supported by advancements in other technologies such as big data analytics, robotics, the Internet of Things, affordable sensors and cameras, drone technology, and widespread internet connectivity across remote fields. By analyzing data on soil management, including temperature, weather, soil conditions, moisture, and historical crop performance, AI systems can offer predictive insights on the best crops to plant, as well as the optimal planting and harvesting times for specific regions. This will not only boost crop yields but also reduce the consumption of water, fertilizers, and pesticides. The application of AI can also help minimize the environmental impact, enhance worker safety, lower food prices, and ensure that food production can meet the demands of the growing population.

Precision agriculture, or precision farming, is an agricultural management approach that utilizes information technology to ensure crops and soil receive precise treatments for optimal health and productivity [1–3]. This approach represents a major shift from traditional farming practices by incorporating advanced technologies such as AI to boost agricultural productivity and sustainability [4, 5].

✉ Garima Gupta, Garima.gupta@iilm.edu | [1]Department of Biotechnology, IILM University, Greater Noida, Uttar Pradesh, India.

In precision agriculture, AI and ML-based surveillance systems offer valuable insights for monitoring crops, detecting pests, and diagnosing soil issues, helping farmers plant seeds at the ideal time for optimal yield. Weeds pose a significant threat to agriculture by reducing crop yields, invading plants, suffocating pastures, and, in rare cases, harming livestock. AI sensors can identify areas affected by weeds and recommend the most effective herbicide for treatment. Additionally, AI systems can predict weather patterns, assess crop health, and identify issues like diseases, pests, or nutrient deficiencies. AI-powered drones allow farmers to monitor crop health, with experts analyzing drone images to generate reports on the farm's condition, aiding pest control efforts. Some farmers are now employing agricultural robots to handle labor-intensive tasks, which help reduce costs associated with manual labor and lighten workers' physical burden. This paper primarily focuses on exploring the various applications of AI in agriculture.

AI technology enables farmers to make more informed decisions, which can lead to greater efficiency in both crop and livestock production. It plays a transformative role in modern agriculture, using data and machine learning to optimize farming practices, predict outcomes, and enhance resource management by crop monitoring, soil analysis, predictive analytics, crop disease, weed and pest detection, all contributing to significant improvements in agricultural efficiency and sustainability (Fig. 1) [6].

This review aims to explore the various applications of AI in precision agriculture, highlighting key technologies, benefits, challenges, and future trends. By examining real-world case studies and implementations, this article provides a comprehensive overview of how AI is revolutionizing the agricultural sector. Agriculture and AI can play a crucial role in addressing future food demand by increasing food production, minimizing waste, and optimizing resource use. As the global population grows, these technologies are essential for ensuring sustainable and sufficient food supplies. AI-driven tools, such as predictive analytics and precision farming, help farmers optimize crop management by analyzing soil conditions, weather patterns, and crop health. This enables them to determine the best planting times, irrigation schedules, and fertilization strategies, leading to higher crop yields per acre and better use of available land. By utilizing data from sensors, drones, and satellites, AI systems can recommend the precise amounts of water, nutrients, and pesticides required at specific times, which reduces waste and minimizes environmental impact. AI can also quickly identify early signs of diseases or pest infestations through image recognition and machine learning, enabling more targeted interventions and reducing crop loss and pesticide usage. AI improves food supply chains by predicting demand, enhancing storage and transportation logistics, and cutting down on food waste. It also promotes sustainable farming practices by recommending methods that improve soil health, reduce carbon emissions, and conserve biodiversity. Through continuous monitoring of environmental factors, AI provides insights that help farmers balance land preservation with increased food production.

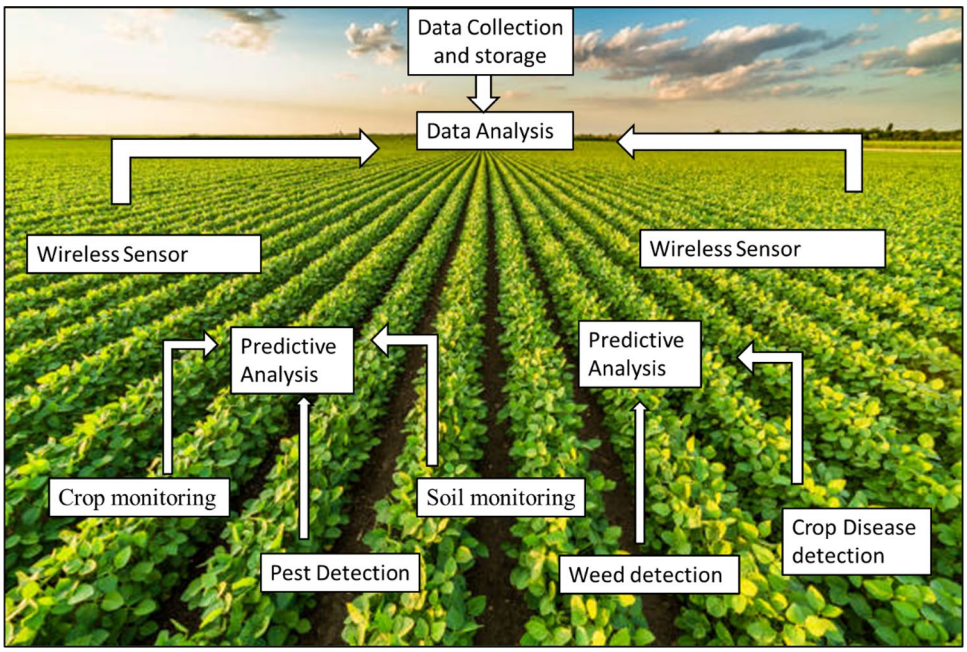


Fig. 1 Process of AI and ML in predictive analysis of agricultural issues

Furthermore, AI-driven automation helps farmers manage large-scale operations more efficiently, lowering labor costs and boosting overall output. It also supports farmers in adapting to climate change by analyzing vast amounts of environmental data to predict weather patterns, droughts, and other climate shifts [7, 8].

In summary, AI can enhance efficiency, sustainability, and adaptability in agriculture, offering innovative solutions to produce more food with fewer resources, reduce waste, and ensure food security in a rapidly changing world. With ongoing advancements in AI technology, agriculture will be better equipped to meet future food demand while reducing its environmental impact.

2 Overview of AI technologies in agriculture

Although there are various technologies based on AI, the most prevalent are categorized below in Table 1 comprehensively provides information about the applications of AI in Precision Agriculture.

3 Key applications of AI in precision agriculture

There are various applications of AI in precision agriculture as can be observed in Fig. 2**.** Detailed subsections provide more information about these applications.

3.1 Crop and soil monitoring

AI-powered remote sensing and satellite imagery are used for detailed crop and soil monitoring. These technologies help farmers assess soil health, manage nutrients, and monitor crop growth stages [42–45]. Crop Monitoring and Management by AI involves the utilization of various data sources and algorithms to optimize agricultural practices. Through the integration of technologies such as satellite imagery, drones, and IoT sensors, AI enables real-time monitoring of crop health, growth patterns, and environmental conditions [46–48]. This allows farmers to detect issues like pest infestations, nutrient deficiencies, or diseases at early stages, facilitating timely intervention to mitigate crop losses and optimize yields [49–52].

AI algorithms analyze vast amounts of data collected from these sources, applying machine learning and computer vision techniques to identify patterns and anomalies in crop development [53–55]. For example, AI can detect subtle changes in plant coloration or leaf texture indicating stress or disease, which may not be apparent to the naked eye. By processing this data, AI systems provide actionable insights to farmers, enabling them to make informed decisions about irrigation, fertilization, pest control, and other management practices [56–58]. Moreover, AI-driven crop monitoring platforms often incorporate predictive modelling capabilities, leveraging historical data on weather conditions, soil composition, and agricultural practices to forecast future crop performance [59]. These predictive analytics help farmers optimize planting schedules, determine optimal harvest times, and allocate resources more efficiently, ultimately enhancing productivity and profitability [59–61].

Overall, Crop Monitoring and Management by AI represents a transformative approach to agriculture, empowering farmers with advanced technologies and data-driven insights to optimize crop production while minimizing resource inputs and environmental impact.

3.1.1 Crop disease detection, pest control, and management

AI systems can detect early signs of pest infestations and plant diseases. Predictive analytics enable proactive management, reducing the reliance on chemical pesticides and minimizing crop losses [62]. Weed and Pest Control by AI offers targeted and environmentally friendly solutions to manage weeds and pests in agriculture. This application utilizes AI algorithms and advanced sensing technologies to accurately identify and selectively treat weed infestations and pest outbreaks, minimizing the use of chemical inputs and reducing environmental impact [34, 63, 64].

Artificial Intelligence (AI) has emerged as a transformative tool in precision agriculture, significantly enhancing crop disease detection, pest control, and overall management strategies. The integration of AI technologies allows for more accurate and efficient monitoring, diagnosis, and intervention, leading to improved crop health and yield.

Table 1 Various AI technologies/methods/models used in precision agriculture

Category	Technology/method	Applications	Functions	Benefits	References
Machine Learning (ML)	Predictive Models	Crop yield prediction, resource optimization, disease detection	Analyzing historical and real-time data to forecast crop performance and optimize agricultural inputs	Enhanced accuracy in decision-making, optimized resource use, and improved crop productivity	[9]
Deep Learning (DL)	CNNs	Disease detection	Identifying crop diseases through image analysis of symptoms such as discoloration and lesions	Early detection, timely intervention, and reduced crop loss	[10]
Computer Vision	Image Processing	Monitoring crop health, pest detection, weed identification	Processing images from satellites and drones for crop monitoring, pest identification, and targeted herbicide application	Automated and precise crop assessment, reduced chemical usage	[11]
Robotics and Automation	Autonomous Farming Vehicles	Planting, spraying, harvesting	Employing robots and autonomous machines for tasks like planting, spraying pesticides, and harvesting crops	Increased efficiency, reduced labor dependency, and precision farming operations	[12, 13]
Natural Language Processing (NLP)	Advisory Systems	Real-time farming advice	Delivering personalized farming recommendations via chatbots and virtual assistants	Improved decision-making and productivity	[14, 15] [9]
Predictive Analytics	Irrigation Management	Forecasting water requirements	Using weather and soil data to optimize irrigation schedules and conserve water	Enhanced water use efficiency, conservation of resources, and better crop health	[16]
Drones and UAVs	Field Monitoring	Monitoring crop health, pest infestations, and water stress	Capturing high-resolution images and analyzing field data for comprehensive monitoring	Timely interventions, reduced monitoring costs, and enhanced crop management	[17, 18]
Genetic Algorithms	Crop Breeding	Development of high-yield, resilient crop varieties	Accelerating the selection of desirable crop traits through AI-driven genetic analysis	Improved food security and resilience to environmental changes	[19, 20]
Fuzzy Logic	Precision Fertilization	Determining optimal fertilizer application	Applying fertilizers based on variable and uncertain conditions analyzed through fuzzy logic systems	Reduced fertilizer waste, improved crop quality, and minimized environmental impact	[21–23]
Reinforcement Learning	Autonomous Irrigation Systems	Optimizing water use	Controlling irrigation systems to maximize yield while minimizing water consumption	Significant water savings and improved crop productivity	[24, 25]
IoT and Sensor Networks	Real-time Data Collection	Soil moisture tracking, weather monitoring, crop health assessment	Collecting and analyzing data through IoT-enabled sensors to inform irrigation, fertilization, and pest management strategies	Real-time insights, optimized irrigation, and reduced resource wastage	[26]

Discover Agriculture (2025) 3:61 | https://doi.org/10.1007/s44279-025-00220-9

Table 1 (continued)

Category	Technology/method	Applications	Functions	Benefits	References
Supply Chain Optimization	Blockchain and GIS	Post-harvest management, logistics optimization	Managing inventory, forecasting demand, optimizing transportation routes, and ensuring product traceability	Reduced food waste, better market prices, and efficient supply chain management	[27]
Climate Adaptation	AI Models	Predicting climate impact on agriculture	Analyzing weather patterns and recommending adaptive strategies for climate resilience	Mitigation of risks, adaptive planning, and enhanced sustainability	[28–30]
Vertical Farming	Growth Condition Optimization	Urban and controlled agriculture	Monitoring and automating growth conditions such as light, temperature, and humidity in indoor farming setups	Higher yields in limited spaces, resource-efficient farming	[26, 31]
Soil Microbiome Analysis	AI-Driven Assessment	Improving crop-soil interaction	Analyzing soil microbiome data to optimize soil health and nutrient availability	Enhanced soil fertility and sustainable farming practices	[32, 33]
Weed Management	CNNs, Drones, Robots	Weed detection and removal	Identifying weed infestations and guiding precision sprayers or mechanical weed removal robots	Reduced herbicide usage, cost efficiency, and environmentally friendly practices	[34, 35]
Pest Management	Machine Learning, Vision Systems	Detecting and managing pest populations	Using AI algorithms to classify pests, monitor populations, and develop targeted control strategies	Improved pest control, reduced crop loss, and decreased reliance on chemical pesticides	[36, 37] [9]
Integrated Crop Management	Data Integration Systems	Disease and pest control, resource optimization	Combining AI technologies to provide real-time insights and predictive analytics for integrated management strategies	Holistic crop management, minimized environmental impact, and optimized input usage	[38, 39] [10]
Resource Management	Decision Support Systems	Optimizing farm operations and resource use	Leveraging multiple data sources (e.g., weather, soil health) for actionable insights	Enhanced productivity, profitability, and sustainability in agriculture	[40, 41]

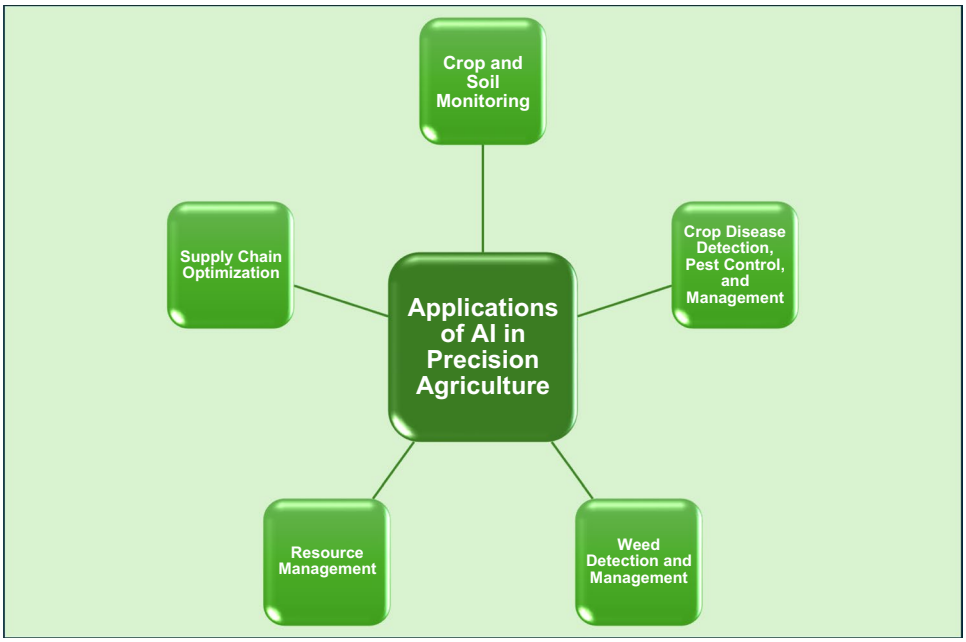


Fig. 2 Applications of AI in Precision Agriculture

3.1.2 AI in crop disease detection

AI-driven approaches for crop disease detection leverage advanced image analysis and machine learning algorithms to identify and diagnose plant diseases (Table 3). Convolutional Neural Networks (CNNs) are particularly effective in this domain. They analyze images of crops to detect visual symptoms of diseases such as discoloration, lesions, and abnormal growth patterns [65–67]. These models are trained on extensive datasets, enabling them to recognize disease-specific features with high precision.

3.2 AI in pest control

AI plays a highly important role in pest control by utilizing machine learning and computer vision to detect and manage pest populations (Table 2). Automated systems which are equipped with high resolution cameras and dedicated sensors capture images of crops to identify pests and their damage. Machine learning algorithms analyze these images to classify pests and assess their impact [68, 69]. This enables the development of precise pest management strategies, such as targeted pesticide application or biologically controlled methods.

3.3 Integrated crop management

Combining AI technologies for crop disease detection and pest control enhances overall crop management. AI systems provide real-time monitoring and predictive analytics, enabling farmers to implement integrated management strategies. For instance, AI can recommend specific treatments based on disease and pest data, optimizing the use of fungicides, herbicides, and pesticides while minimizing environmental impact [70, 71].

Table 2 AI technologies for pest control

Technology/method	Description
Machine Learning Algorithms	Algorithms that classify and predict pest infestations based on image and sensor data
Computer Vision Systems	Systems that use cameras and sensors to detect pests and monitor their damage
Automated Pest Monitoring	Technologies for real-time monitoring and analysis of pest populations using AI
Precision Application Systems	Systems that apply pesticides selectively based on AI-driven recommendations

3.3.1 Benefits of AI in integrated crop management

1. **Early Detection and Rapid Response**: AI technologies enable the early detection of diseases and pests, allowing for swift intervention and reducing the potential for widespread damage [72, 73]. Early detection is crucial for effective management and minimizing yield losses.
2. **Targeted Treatments**: AI facilitates precise application of treatments, such as fungicides and pesticides, by analyzing disease and pest data to recommend specific interventions. This targeted approach reduces chemical usage and mitigates negative environmental impacts [74].
3. **Cost Efficiency:** AI-driven systems can lower the overall cost of weed management by minimizing the volume of herbicides used and reducing labor costs associated with manual weeding [34, 35]. Automated systems, such as robotic weeders and precision sprayers, enhance operational efficiency and reduce long-term expenses.
4. **Data Driven Decision Making:** AI integrates data from multiple sources like weather conditions, soil health, and weed population dynamics, to provide actionable insights for weed management. This comprehensive approach enables farmers to make informed decisions and adapt their management practices to changing conditions [37, 75].

Overall, Crop Disease Detection and Management by AI offers significant benefits in terms of early detection, targeted intervention, and data-driven decision-making (Fig. 3). By leveraging AI algorithms and sensing technologies, farmers can improve disease management practices, reduce yield losses, and enhance the resilience of agricultural systems against disease outbreaks [77].

AI models can identify patterns and correlations that influence crop yields. These models can then generate predictive analytics that enable farmers to make informed decisions about planting schedules, irrigation strategies, fertilization regimes, and pest management practices [78]. For example, AI algorithms can analyze historical weather data to identify optimal planting dates and predict the impact of climate variability on crop growth. By considering factors such as temperature, precipitation, and solar radiation, these models can estimate crop yields under different environmental scenarios, helping farmers mitigate risks and maximize productivity [79–81].

Moreover, AI-driven predictive analytics enable farmers to optimize resource allocation by identifying areas of the field with the highest yield potential. By generating yield maps based on soil variability, topography, and historical performance, these models help farmers implement variable rate application (VRA) techniques, tailoring inputs such as fertilizers and pesticides to specific crop requirements [82–84].

Ultimately, Predictive Analytics for Yield Optimization by AI empowers farmers to make data-driven decisions that enhance productivity, profitability, and sustainability in agriculture [85, 86]. By leveraging advanced analytics and predictive modelling capabilities, farmers can optimize crop yields while minimizing resource inputs and environmental impact [85, 87].

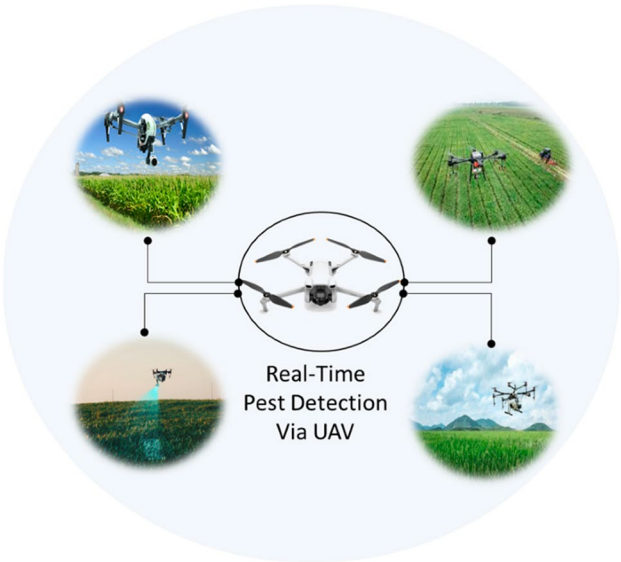


Fig. 3 Pest control and disease management utilizing human and human-less drone facility [76]

3.4 Weed detection and management

Weed detection and management have undergone transformative changes with the advent of artificial intelligence (AI), leading to more precise and environmentally sustainable agricultural practices. AI technologies offer advanced solutions for identifying, classifying, and managing weed populations, thereby reducing the reliance on chemical herbicides and enhancing overall crop productivity.

3.4.1 AI technologies for weed detection

The core of AI-powered weed detection involves machine learning algorithms that process and analyze high-resolution images captured by various sensors, including drones, cameras, and ground-based imaging systems (Table 3). Convolutional Neural Networks (CNNs) are particularly effective for this purpose. CNNs are designed to automatically and adaptively learn spatial hierarchies of features from images, making them well-suited for distinguishing between crops and weeds based on visual characteristics such as leaf shape, size, and color [88, 89]. These algorithms are trained on large datasets of annotated images, enabling them to recognize different weed species with high accuracy.

3.4.2 Targeted weed management

Once weeds are detected, AI systems can recommend targeted management strategies. These systems use algorithms to analyze weed distribution patterns and suggest precise herbicide applications (Fig. 4). For example, AI can guide precision sprayers to apply herbicides only in areas where weeds are present, thus minimizing chemical use and reducing potential damage to crops [90, 91]. Additionally, AI can control autonomous weeding robots that mechanically remove weeds based on real-time detection, reducing the need for chemical treatments and supporting organic farming practices [92].

3.4.3 Advantages of AI in weed management

1. **Increased Precision**: AI allows for the accurate identification of weed species and their growth stages, leading to more effective and targeted weed control strategies [93]. This precision helps in minimizing herbicide use and reducing the risk of resistance development in weed populations.
2. **Reduced Environmental Impact**: By optimizing herbicide application and promoting mechanical weeding methods, AI contributes to a reduction in chemical runoff and soil degradation. This shift towards more sustainable practices supports environmental conservation and reduces the ecological footprint of farming [93].
3. **Cost Efficiency**: AI-driven systems can lower the overall cost of weed management by minimizing the volume of herbicides used and reducing labor costs associated with manual weeding [93]. Automated systems, such as robotic weeders and precision sprayers, enhance operational efficiency and reduce long-term expenses.
4. **Data-Driven Decision Making**: AI integrates data from multiple sources, including weather conditions, soil health, and weed population dynamics, to provide actionable insights for weed management [93]. This overall comprehended approach enables our farmers to make pre-guided and informed decisions and adapt their management practices to ever changing environmental conditions.

Table 3 Key AI technologies and methods in weed and crop disease detection

Technology/method	Description
Convolutional Neural Networks (CNNs)	Deep learning models used for accurate image of weed detection and classifying disease symptoms
Support Vector Machines (SVMs)	Machine learning method that classifies images by finding the optimal hyperplane separating classes
Image Processing Techniques	Methods used to enhance image quality and extract features for more accurate weed identification and disease-related features
Drones and Ground-Based Sensors	Technologies used to capture detailed field images for weed detection and monitoring crop health over large areas
Data Integration Systems	Systems that combine data from various sources to improve disease detection and management

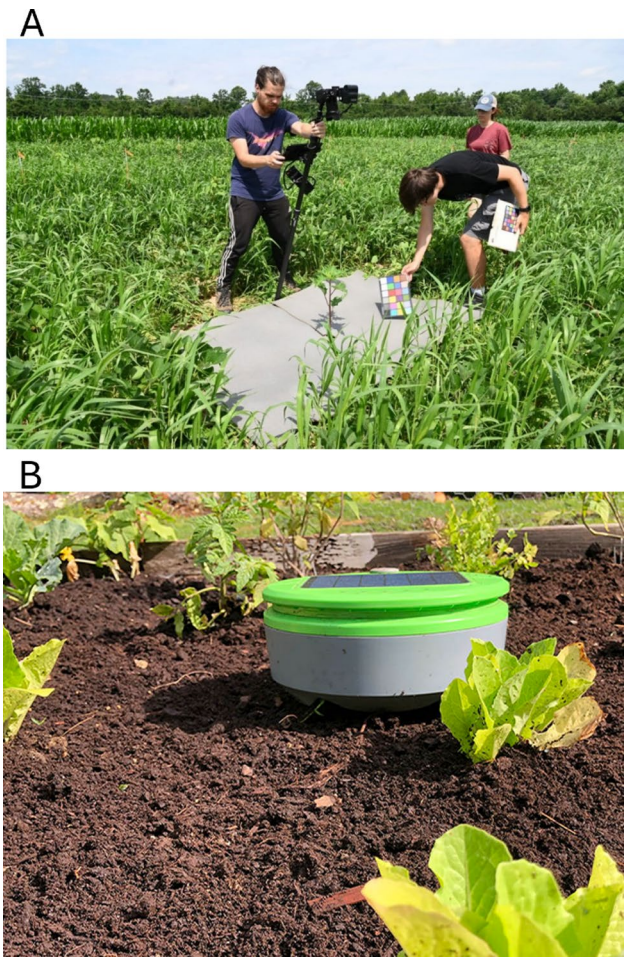


Fig. 4 An AI-powered weed detection and management system. The above figure **A** illustrates the process from image capture to targeted treatment recommendations. The below figure **B** shows a solar powered robot to dig-out the detected weeds (https://growiwm.org/what-is-precision-weed-management/)

3.5 Resource management

AI-based irrigation systems optimize water usage by analyzing soil moisture data. Precision fertilization ensures the right amount of nutrients is applied at the right time, enhancing crop growth while reducing environmental impact [94]. Data-Driven Decision Support Systems by AI revolutionize agricultural decision-making by leveraging advanced algorithms to analyze vast amounts of data and provide actionable insights to farmers. These systems integrate data from multiple sources, including satellite imagery, weather forecasts, soil sensors, crop health monitors, and historical farm records, to enable informed and timely decision-making across various aspects of farm management [95].

One of the key features is their ability to process and analyze complex data sets to extract valuable insights. AI algorithms, such as machine learning and predictive analytics, can identify patterns, correlations, and trends in the data, helping farmers understand the factors influencing crop performance, resource use, and profitability [40]. Moreover, Data-Driven Decision Support Systems by AI provide personalized recommendations tailored to the specific needs and conditions of each farm. By considering factors such as soil type, climate, crop rotation history, and market prices, these systems can generate customized management plans that optimize resource allocation, minimize risks, and maximize returns [96].

Additionally, it enables farmers to make proactive decisions based on instantaneous data and predictive analytics. By monitoring field conditions, crop growth, and weather forecasts in real-time, AI-driven systems can alert farmers to potential risks, such as pest outbreaks, nutrient deficiencies, or adverse weather events, allowing them to take preventive measures and mitigate losses [78]. Furthermore, resource management by AI facilitates the optimization of farm operations and sustainability practices. By analyzing data on resource use, environmental impact, and regulatory compliance, these systems can identify opportunities for efficiency improvements, waste reduction, and sustainable practices adoption [97].

Overall, farmers with valuable insights and recommendations that enhance productivity, profitability, and sustainability in agriculture. By leveraging AI algorithms to analyze data and provide actionable insights, producers can make informed decisions that optimize farm performance and address the challenges of modern agriculture [98].

3.6 Supply chain optimization

AI improves post-harvest management through efficient logistics and demand forecasting. This helps in reducing food waste, optimizing supply chains, and ensuring better market prices for farmers [99]. Supply chain management (SCM) in precision agriculture involves the integration of advanced technologies and data analytics to optimize the flow of goods, information, and finances throughout the agricultural production and distribution process [100]. Precision agriculture bank on wide-ranging data collection from numerous sources such as sensors, satellites, and weather stations. This data is crucial for making informed decisions regarding crop management, resource allocation, and logistics planning [100].

Real-time management and monitoring of inventory levels for agricultural inputs such as seeds, fertilizers, and pesticides are facilitated by IoT and AI technologies. This ensures timely availability and prevents stockouts, optimizing production efficiency [53]. AI algorithms and geographic information systems (GIS) are used to optimize transportation routes and logistics operations in agriculture, reducing costs and minimizing environmental impact. Technologies like blockchain are employed for traceability purposes in agriculture, ensuring product quality and compliance with food safety standards from farm to table [101]. Predictive analytics and AI models help in identifying and mitigating risks related to weather variability, pests, diseases, and market fluctuations, enhancing supply chain resilience. Precision agriculture practices aim to minimize environmental impact through optimized resource use and reduced chemical inputs. SCM strategies support sustainable practices across the supply chain, contributing to environmental stewardship [102].

Effective SCM in precision agriculture requires collaboration among stakeholders including farmers, suppliers, distributors, and retailers. Integrated digital platforms facilitate communication and coordination, improving overall supply chain efficiency. Continuous monitoring and analysis of supply chain performance metrics enable ongoing optimization and improvement of processes in precision agriculture [103].

In conclusion, SCM in precision agriculture leverages technological advancements and data-driven insights to enhance efficiency, sustainability, and resilience across the agricultural supply chain, addressing contemporary challenges in food production and distribution.

4 Case studies and real-world implementations

4.1 Case study 1: crop monitoring with drones

A notable implementation of AI in agriculture is the use of flying drones equipped with multispectral cameras to monitor crop health. For instance, a vineyard in California used drones to capture images of grapevines, which were then analyzed using AI to detect signs of disease and water stress. This approach led to a twenty percent increase in grape yield and a substantial reduction in water usage [104]. The crop monitoring operations can be performed by either remote sensing technology or by seedling emergence analysis. The effect of employing drones for monitoring crop health was analyzed and the data suggested that the crop health was improved, and the loss of crops was reduced as the monitoring was done effectively (Fig. 5).

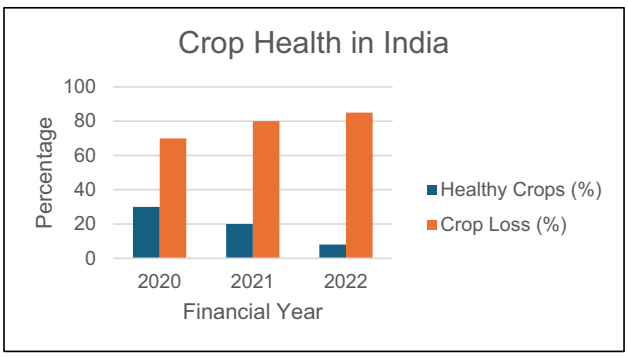


Fig. 5 Analysis of crop health and crop loss by implementing drones to monitor crop health

4.2 Remote sensing technology

Remote sensing has become a useful tool for timely monitoring as well as giving an accurate picture of the agricultural industry with high repeat and accuracy swell as numerous GNSS and GIS technology. There is a need for remote sensing tools that cause agricultural to be susceptible to soil, weather and other chemical changes. Therefore, agricultural operations must be constantly monitored. Remote sensing applications are basically centered on the use of passive and active systems to capture the EM radiation reflected from the crops and soil as well as various crop and vegetation parameters. Crop yield forecasting to be accurate lies on the proper interpretation of NIR red reflection to know the exact time to harvest before the crop season comes to an end. In addition to that microwave radiation is also used with remote sensing systems for light beating and many spectroscopy applications while remote sensing is also used for measuring plant water stress using thermal derivatives which is when the leaf or canopy is heated, and observations are made.

Various plant parameters can be analyzed by getting the ratio of reflected light in red region and near infrared region. These parameters include nitrogen or chlorophyll content, spectral or leaf area index etc. The ability of remote sensing to provide detailed crop data has revolutionized the agriculture industry. Groundwater is a vital natural resource which plays a critical role in sustaining agriculture and remote sensing is heavily used in this area [105].

Site specific weed management (SSWM) technique provides the desired amount of herbicide at the exact location within the specified time. This technique is divided into four major parts which are weed sensing and mapping, selection of the chemical treatment, spraying of the chemical, and recording the data. Spraying of herbicide reduces the weed growth. The density of weed is estimated to calculate the dose of chemicals. This technique helps in reduction of amount of herbicide applied thus reducing the cost of weed management.

4.3 Analysis of seedling emergence

Analysis of seedling emergence can be detected by imaging with the drones in a timely manner as the window period to replant the seedlings in case of late or no germination is very short. Sprouting can be detected by high resolution images to identify zones with ineffective germinations. The leaf size of the newly germinated plant will provide the vegetation index. Once the complete mapping of the field is over, the density of the seedlings is compared with manually validated count of seedlings. The low seedling density zones are considered for replanting of seeds.

4.4 Case study 2: pest management

Pesticides increase the crop quality and yield but the conventional techniques for their application causes damage due to unequal spraying of pesticide, longer time and health issues to the farmers. This has led to increased applications of drone-based spraying of pesticides as it reduces the cost of spraying and damage of crops due to even distribution of pesticide and time management. This technique can further detect the regions which are more infected with the pests and can regulate the dose of pesticides to be sprayed accordingly.

UAVs are used extensively these days as they enhance the operations by spraying the pesticide in less time, reduces the damage as it does not harm the crop mechanically while changing the path, and no human casualty even at low altitudes as it operates without pilots. It is capable to dispense solid and liquid both the forms of chemicals, making it a more precise and secure mode of pesticide spraying (Fig. 6).



Fig. 6 Aerial spraying of pesticides using drones on growing crops for pest and weed management (https://iotechworld.com/drones-for-spraying-pesticides-opportunities-and-challenges/)

4.5 UAV based pesticide application

Wireless network systems are employed while spraying chemicals by drones as it helps in managing the operation in a precise and secure manner. Using such technology has the major advantage of adjusting the path of the drone based on the changing weather conditions, thereby resolving the issue of drifting out or overlapping pesticides with the aid of constant feedback technology. A series of parallel grids spread across the crop field make up WSN.

The communicating sensors detect the amount of pesticide deposited at a site and the wind direction in order to instruct the drone to change its track as per the requirement. The sensors detect the amount of chemical deposited at a site by identifying one compound and determining its threshold concentration. The wind direction helps the drone to adjust its track so the sprayed chemical should be deposited at the desired site.

5 Challenges

5.1 Collection of data

Despite the advancement of precision agriculture over the past thirty years, two major challenges have impeded the widespread use of machine learning predictions in the field. First, a large number of farmers and growers have not embraced the benefits of precision agriculture, with various studies and reasons explaining this lack of adoption. Second, implementing precision agriculture technologies does not necessarily involve gathering all essential data through IoT or other means for predictive purposes. The second factor could be a critical barrier to the practical use of AI from a technical perspective. Agricultural activities inherently involve some degree of uncertainty (referred to as irreducible error in AI terms) due to environmental factors beyond our control. As a result, continuous collaboration is needed between data scientists with expertise in agriculture and farmers, growers, agronomists, and consultants. This mutual knowledge and understanding are essential for creating models that offer dependable benefits for farmers and growers.

5.2 Data ownership and privacy

Data is primarily owned and accessed by producers, including farmers, greenhouse managers, breeders, and agronomists, but this doesn't tell the whole story. While these owners can access some essential data, they often lack immediate access to other valuable information, such as historical environmental data or satellite imagery, unless they pay for it and receive training on how to use it. This gap—especially the limited access to environmental and satellite data for farmers—can be addressed by data scientists and data engineers, who are skilled in collecting and integrating data from various sources.

Data privacy is another complex challenge when it comes to sharing farming data. Methods such as anonymization, encryption, and aggregation can help address concerns related to intellectual property while implementing AI on a large scale in agriculture. Non-disclosure agreements (NDAs) and AI techniques are available to analyze the data and extract valuable insights without infringing on the intellectual property of farming data, especially when the data's granularity or spatial aspects are important.

5.3 Unorganized agricultural data

Even if data is comprehensively collected and a farmer (or advisor) has access to all relevant farm data, the lack of centralization in data collection across farms limits the potential for collective knowledge and insights that AI-based techniques could provide. The FAO estimates that there are 570 million farms worldwide. So, how can a data scientist make use of this vast amount of data to improve yields? One solution, without violating privacy regulations, is to use satellite imagery data. Historical satellite data, with a resolution as high as 30 cm, can be purchased, or lower-resolution data is often available for free globally. This allows computer vision experts and data scientists to extract useful features (such as NDVI and NDWI) from historical satellite images to train models that predict yield, disease, or stress on farms.

5.4 Cost of incorporating AI in agriculture

The high cost of change is especially significant in the farming industry. Acting on incorrect recommendations in agriculture can result in a loss of crop yield for an entire season. One way to address this issue is by implementing changes

on a smaller scale, even if the farmer operates on a large scale. This could involve adjusting a small portion of the farm or gradually introducing changes over several farming seasons while incorporating feedback along the way.

5.5 Lack of hands-on experience with latest technologies

The level of technological advancement in the agricultural industry varies across regions. While some areas may fully benefit from AI, others, especially in countries with emerging agricultural technologies, face significant barriers. Technology companies looking to enter these markets may need to take a forward-thinking approach. Beyond offering their products, they must provide training and ongoing support to farmers and agribusiness owners willing to adopt new solutions.

5.6 Reluctance to adopt new technologies and processes

A lack of awareness often leads to resistance to adopting new technologies, making it difficult for farmers to fully embrace AI, even when it offers clear benefits. This resistance to change, coupled with a reluctance to take risks with new methods, slows the evolution of farming practices and limits the sector's profitability. Farmers need to understand that AI is simply a more advanced version of traditional technologies used for field data processing. To encourage adoption, both public and private sectors must provide resources, incentives, and training. Governments should also implement regulations that reassure workers that AI is not a threat.

Finance and Investment: The integration of Artificial Intelligence (AI) in precision agriculture holds great promise for improving crop yields, optimizing resource use, and minimizing environmental impact. However, one of the main challenges in adopting AI on a large scale is the financial investment required to make it viable. These financial barriers are complex, involving high initial costs and uncertainty about the potential return on investment. Many smallholder farmers, particularly in developing countries, have limited access to credit or financing options needed to support the adoption of new technologies. Since AI adoption demands significant upfront investment, farmers without access to affordable credit may struggle to afford AI-driven tools and technologies. Small-scale farmers often depend on traditional financing methods, such as informal loans or family funds, which may fall short of covering the costs of advanced AI systems. Additionally, farmers with limited financial literacy and infrastructure may be hesitant to take on debt for new technologies, especially if the return on investment is not immediately apparent. This uncertainty can deter them from investing in AI, as they may not be confident that the long-term benefits will outweigh the initial costs. AI technologies in agriculture often require a long time to yield significant financial returns, particularly when they focus on enhancing efficiency or sustainability. As such, farmers may be reluctant to invest in technologies when they cannot quickly realize financial benefits. This extended payback period can also present a challenge for investors seeking quicker returns. Startups and smaller companies developing AI solutions for precision agriculture face substantial financial risks and may find it difficult to secure adequate funding due to long development timelines, uncertain returns, and potential market risks. Without strong investor confidence, these companies may struggle to scale their AI solutions. Investors may also be cautious about funding AI projects in agriculture because of the uncertainty surrounding market acceptance and the relatively slow adoption of technology in traditional farming industries.

5.7 High upfront costs

While AI can be cost-effective in the medium to long term, the initial investment required can be prohibitively high. For many agribusinesses, particularly small-scale farmers and those in developing countries, adopting AI may appear financially impractical. Implementing AI in agriculture demands substantial capital for both hardware and software, such as drones, sensors, IoT devices, satellite imagery, and advanced computing infrastructure to gather and analyze data. The upfront costs of these technologies can be especially burdensome for small-scale farmers or those in less developed regions. Additionally, integrating AI systems into existing farm management practices requires further investment in developing new workflows and systems, adding to the initial financial strain. However, as technology evolves, the costs of implementing AI in agriculture are expected to decrease. Moreover, businesses may explore funding options through private investments or government grants to help offset the initial costs.

Education and Skill: Many farmers, particularly in rural or developing areas, may lack the fundamental knowledge of AI, machine learning, or data science. Without a clear understanding of how these technologies work or their potential benefits, adopting them can be slow. Farmers may also hesitate to use AI-driven tools, worrying they are too complex or not suited to their needs. Additionally, there is limited access to training programs, workshops, or

online courses that could help farmers develop their AI skills. Even when resources are available, they may not be tailored to the specific agricultural context, making it challenging for farmers to see how AI can be practically applied.

AI tools often require technical skills, such as data analysis, programming, and an understanding of machine learning principles. For farmers accustomed to traditional methods, this learning curve can be a significant obstacle. Moreover, AI in agriculture relies on data from sensors, drones, weather reports, and soil moisture levels, but many farmers may not have the expertise to collect, analyze, or interpret this data effectively. Without proper data management skills, the full potential of AI-driven solutions may go unrealized. Even when training is offered, there might be a lack of ongoing support to help farmers transition to AI-enhanced agricultural practices. Continuous guidance and troubleshooting are often needed, especially in remote or underserved areas, and this lack of support can make sustained adoption difficult.

Existing training programs and tools may not be customized to fit the environmental or economic conditions of specific regions, meaning what works in one place may not be applicable in another. Therefore, developing localized curricula that address the unique challenges and needs of specific agricultural sectors is essential, though it can be a challenge.

To successfully tackle these obstacles, partnerships with educational institutions are needed to provide accessible training programs for farmers and agricultural professionals. AI solutions should be designed to be user-friendly and easy to incorporate into existing workflows. Additionally, education should be context-sensitive and tailored to the specific agricultural systems in question. Overcoming these challenges will be crucial for effectively integrating AI into agriculture, ensuring the technology is accessible, understandable, and beneficial to the farmers who need it most.

6 Future trends: new emerging applications of AI in precision agriculture

The field of artificial intelligence (AI) is undergoing rapid advancements, with novel applications extending its utility in precision agriculture to address multifaceted challenges such as climate resilience, ecological sustainability, and technological integration in unconventional agricultural systems. These emergent technologies are redefining traditional agricultural paradigms, offering transformative solutions to enhance the resilience, efficiency, and sustainability of agronomic practices.

6.1 Climate adaptation

Agricultural systems are increasingly vulnerable to the deleterious effects of climate change. Advanced AI-driven predictive models are being developed to quantify and forecast the impacts of fluctuating climatic variables on crop phenology and productivity. These models synthesize historical meteorological data, edaphic factors, and agronomic records to generate actionable insights aimed at mitigating risks associated with abiotic stresses, including droughts, floods, and heatwaves. For instance, AI algorithms can recommend adaptive strategies such as cultivar selection and optimal sowing schedules tailored to projected environmental conditions. Such applications not only fortify agricultural systems against climatic perturbations but also enhance resource-use efficiency, aligning with sustainable agricultural objectives [28, 39, 106, 107].

6.2 Precision livestock farming

AI is spearheading advancements in precision livestock management by enabling real-time monitoring and optimization of animal health, behavior, and nutritional intake. Integrating advanced biosensors and wearable technologies, AI systems capture a myriad of physiological and behavioral metrics, including body temperature, locomotion patterns, and feeding behaviors. Analytical algorithms process this high-dimensional data to detect deviations indicative of subclinical diseases or stress, facilitating prompt and targeted interventions. Furthermore, AI-powered feed optimization systems dynamically calibrate dietary formulations to match individual animal requirements, enhancing feed conversion efficiency and reducing the ecological footprint of livestock farming operations. This confluence of AI and livestock management underscores a paradigm shift towards data-intensive, welfare-centric, and environmentally sustainable animal husbandry [108, 109].

6.3 Vertical farming and urban agriculture

The burgeoning demand for sustainable food production within urbanized environments has catalyzed the adoption of vertical farming and controlled-environment agriculture (CEA). AI systems are instrumental in optimizing the multifactorial parameters that govern crop productivity in these systems, including photoperiod, temperature, relative humidity, and nutrient delivery. Leveraging real-time sensor data, machine learning algorithms enable dynamic modulation of growth conditions to maximize biomass accumulation and resource-use efficiency. For example, AI-enabled lighting systems utilize spectral optimization to enhance photosynthetic efficiency while minimizing energy consumption. Such innovations render vertical farming a scalable solution to urban food security challenges, with reduced land and water requirements compared to conventional agricultural systems [26, 31].

6.4 Soil microbiome analysis

The soil microbiome, comprising a complex assemblage of microorganisms, plays a pivotal role in driving biogeochemical processes and plant–microbe interactions. AI technologies are now being deployed to decode the functional potential of soil microbial communities through the analysis of metagenomic and transcriptomic datasets. These computational frameworks elucidate microbial dynamics and their contributions to nutrient cycling, pathogen suppression, and plant growth promotion. By identifying keystone microbial taxa and their functional traits, AI-driven soil microbiome analyses facilitate the formulation of microbiome-informed agronomic practices, such as targeted microbial inoculation and conservation tillage. This integrative approach not only enhances soil health and crop resilience but also mitigates dependency on synthetic agrochemicals [32, 33, 110, 111].

These emerging AI applications represent a confluence of cutting-edge computational methodologies and agricultural science, offering unprecedented opportunities to revolutionize global agrifood systems. By synergizing traditional agricultural knowledge with advanced technological paradigms, these innovations promise to address the dual imperatives of agricultural productivity and environmental stewardship in an era of unprecedented global challenges [112–114].

7 Conclusion

Agriculture is a labor-intensive field, and with the increasing population and demand for agricultural production, automation is becoming essential. AI plays a crucial role in assisting farmers with various components, technologies, and applications. Predictive analytics and advanced farm and crop management systems ensure crop quality and consistent supply. By utilizing satellite imagery and weather data, businesses can monitor acreage and crop health in real-time. AI, big data, and machine learning technologies help forecast prices, estimate output and yield, and detect pest and disease infestations. They can provide farmers with advice on demand levels, optimal crop varieties for profitability, pesticide use, and future pricing trends. AI emerges as a powerful tool to address the growing complexity of modern agriculture by significantly mitigating resource and labor shortages. It is high time for major corporations to invest in this sector. This review emphasizes the profound impact of AI on precision agriculture, encompassing crop monitoring, pest management, resource optimization, and supply chain efficiency. It also throws light on the challenges based upon data collection, ownership and privacy which need government policies to resolve these issues. The lack of technically trained manpower in the agriculture sector is another challenge which needs to be addressed by the large corporates by arranging hands on training sessions for the farmers. The future of worldwide agriculture hinges on the effective integration of AI technologies. Ongoing innovation, supportive policies, and collaborative research will propel the agricultural sector towards a more sustainable and efficient future, ensuring global food security and economic growth.

Author contributions G. G. wrote the Introduction, overview of AI in Agriculture, case studies and conclusion. S.K.P. wrote the Applications of AI, benefits, future trends and opportunities. G.G. and S.K.P. reviewed the manuscript.

Funding There is no funding received from any of the funding agencies to conduct this work.

Data availability No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate Both the authors are declaring that they are in consent of putting their names in the manuscript.

Consent for publication Authors hereby grant permission for the publication of their research article titled "Applications of AI in Precision Agriculture" in Discover Journal. We confirm that we hold the rights to this work and that it has not been published elsewhere. We understand that by granting this consent, we are allowing Discover Journal to use, distribute, and archive our article in accordance with their publishing policies.

Competing interests The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

References

1. Joseph GB, McCulloch CE, Sohn JH, Pedoia V, Majumdar S, Link TM. AI MSK clinical applications: cartilage and osteoarthritis. Skeletal Radiol. 2022;51:331–43. https://doi.org/10.1007/s00256-021-03909-2.
2. Lim HR, Khoo KS, Chia WY, Chew KW, Ho S-H, Show PL. Smart microalgae farming with internet-of-things for sustainable agriculture. Biotechnol Adv. 2022;57: 107931. https://doi.org/10.1016/j.biotechadv.2022.107931.
3. Mavridou E, Vrochidou E, Papakostas GA, Pachidis T, Kaburlasos VG. Machine vision systems in precision agriculture for crop farming. J Imaging. 2019. https://doi.org/10.3390/jimaging5120089.
4. Waseem R, Mwalupaso GE, Waseem F, Khan H, Panhwar GM, Shi Y. Adoption of Sustainable agriculture practices in banana farm production: a study from the Sindh region of Pakistan. Int J Environ Res Public Health. 2020. https://doi.org/10.3390/ijerph17103714.
5. Ammann K. Why farming with high tech methods should integrate elements of organic agriculture. N Biotechnol. 2009;25:378–88. https://doi.org/10.1016/j.nbt.2009.06.933.
6. Singh H, Sharma A, Bhardwaj SK, Arya SK, Bhardwaj N, Khatri M. Recent advances in the applications of nano-agrochemicals for sustainable agricultural development. Environ Sci Process Impacts. 2021;23:213–39. https://doi.org/10.1039/d0em00404a.
7. Islam R, Ahmed R, Dey B, Haque MS, Aktar S, Bhuiyan MS, et al. Salinity hazard drives the alteration of occupation, land use and ecosystem service in the coastal areas: evidence from the south-western coastal region of Bangladesh. Heliyon. 2023;9: e18512. https://doi.org/10.1016/j.heliyon.2023.e18512.
8. Dey B, Ador MAH, Haque MMU, Ferdous J, Halim MA, Uddin MB, et al. Strategic insights for sustainable growth of mushroom farming industry in Bangladesh: a comprehensive evaluation using SWOT-AHP and TOPSIS frameworks. Heliyon. 2024;10: e36956. https://doi.org/10.1016/j.heliyon.2024.e36956.
9. Dey B, Ferdous J, Ahmed R, Hossain J. Assessing deep convolutional neural network models and their comparative performance for automated medicinal plant identification from leaf images. Heliyon. 2024;10: e23655. https://doi.org/10.1016/j.heliyon.2023.e23655.
10. Dey B, MasumUlHaque M, Khatun R, Ahmed R. Comparative performance of four CNN-based deep learning variants in detecting Hispa pest, two fungal diseases, and NPK deficiency symptoms of rice (Oryza sativa). Comput Electron Agric. 2022;202:107340. https://doi.org/10.1016/j.compag.2022.107340.
11. Sapkota R, Stenger J, Ostlie M, Flores P. Towards reducing chemical usage for weed control in agriculture using UAS imagery analysis and computer vision techniques. Sci Rep. 2023;13:6548. https://doi.org/10.1038/s41598-023-33042-0.
12. Subeesh A, Mehta CR. Automation and digitization of agriculture using artificial intelligence and internet of things. Artif Intell Agric. 2021;5:278–91. https://doi.org/10.1016/j.aiia.2021.11.004.
13. Kirpach M, Riccoboni A. AI in Agriculture. Engineering mathematics and artificial. Boca Raton: CRC Press; 2023.
14. Suvarchala TL, Chandana P. NLP based cotton crop advisory: a dialogflow-powered Chatbot. Piscataway: IEEE; 2023.
15. Reddy PSV, Prasad KSN. Conversational AI bot based on IoT knowledgebase for smart agriculture. Systems (ICKECS). Piscataway: IEEE; 2024.
16. Delgoda D, Malano H, Saleem SK, Halgamuge MN. Irrigation control based on model predictive control (MPC): formulation of theory and validation using weather forecast data and AQUACROP model. Environ Model Softw. 2016;78:40–53. https://doi.org/10.1016/j.envsoft.2015.12.012.
17. Kardile PB, Dalvi DG, Kalyankar SV. Applications of Digital Sensors and Imaging Techniques in Agriculture and Abiotic Stress Management of Field Crops. In Agricultural and. 2022.
18. Barbedo JGA. A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses. Drones. 2019;3:40. https://doi.org/10.3390/drones3020040.
19. Patil A. Use of artificial intelligence to hasten progress in plant genetics. Intelligence (AI). 2023. https://doi.org/10.20944/preprints202309.1067.v1.
20. Kundu V. Artificial Intelligence (AI): Cultivating innovation in crop breeding. researchgate.net.

21. Prabakaran G, Vaithiyanathan D, Ganesan M. Fuzzy decision support system for improving the crop productivity and efficient use of fertilizers. Comput Electron Agric. 2018;150:88–97. https://doi.org/10.1016/j.compag.2018.03.030.
22. Papadopoulos A, Kalivas D, Hatzichristos T. Decision support system for nitrogen fertilization using fuzzy theory. Comput Electron Agric. 2011;78(2):130–9.
23. Ashraf A, Akram M, Sarwar M. Fuzzy decision support system for fertilizer. Neural Comput Applic. 2014;25:1495–505. https://doi.org/10.1007/s00521-014-1639-4.
24. Ding X, Du W. Optimizing irrigation efficiency using deep reinforcement learning in the field. ACM Trans Sen Netw. 2024;20:1–34. https://doi.org/10.1145/3662182.
25. Yang Y, Hu J, Porter D, Marek T, Heflin K. Deep reinforcement learning-based irrigation scheduling. Tans ASABE. 2020;63(3):549–56.
26. Rathor AS, Choudhury S, Sharma A, Nautiyal P, Shah G. Empowering vertical farming through IoT and AI-Driven technologies: a comprehensive review. Heliyon. 2024;10: e34998. https://doi.org/10.1016/j.heliyon.2024.e34998.
27. Dhal SB, Kar D. Transforming agricultural productivity with AI-driven forecasting: innovations in food security and supply chain optimization. Forecasting. 2024;6:925–51. https://doi.org/10.3390/forecast6040046.
28. Kumar Sharma R, Dhillon J, Kumar P, Raja Reddy K, Reed V, Dodds DM, et al. Modelling the climate change and cotton yield relationship in Mississippi: autoregressive distributed lag approach. Ecol Indic. 2024;166: 112573. https://doi.org/10.1016/j.ecolind.2024.112573.
29. Ureta C, González EJ, Espinosa A, Trueba A, Piñeyro-Nelson A, Álvarez-Buylla ER. Maize yield in Mexico under climate change. Agric Syst. 2020;177: 102697. https://doi.org/10.1016/j.agsy.2019.102697.
30. Khanal U, Wilson C, Rahman S, Lee BL, Hoang V-N. Smallholder farmers' adaptation to climate change and its potential contribution to UN's sustainable development goals of zero hunger and no poverty. J Clean Prod. 2021;281: 124999. https://doi.org/10.1016/j.jclepro.2020.124999.
31. Sowmya C, Anand M, Indu Rani C, Amuthaselvi G, Janaki P. Recent developments and inventive approaches in vertical farming. Front Sustain Food Syst. 2024. https://doi.org/10.3389/fsufs.2024.1400787.
32. Anthony WE, Allison SD, Broderick CM, Chavez Rodriguez L, Clum A, Cross H, et al. From soil to sequence: filling the critical gap in genome-resolved metagenomics is essential to the future of soil microbial ecology. Environ Microbiome. 2024;19:56. https://doi.org/10.1186/s40793-024-00599-w.
33. Garg D, Patel N, Rawat A, Rosado AS. Cutting edge tools in the field of soil microbiology. Curr Res Microbial Sci. 2024;6: 100226. https://doi.org/10.1016/j.crmicr.2024.100226.
34. Vasileiou M, Kyrgiakos LS, Kleisiari C, Kleftodimos G, Vlontzos G, Belhouchette H, et al. Transforming weed management in sustainable agriculture with artificial intelligence: a systematic literature review towards weed identification and deep learning. Crop Prot. 2024;176: 106522. https://doi.org/10.1016/j.cropro.2023.106522.
35. Muchhadiya RM, Kumawat PD, Gohil BS. Precision weed management using artificial intelligence tools and techniques for sustainable agriculture. Agric Food e-Newslett. 2024;6:606.
36. Deguine J-P, Aubertot J-N, Flor RJ, Lescourret F, Wyckhuys KAG, Ratnadass A. Integrated pest management: good intentions, hard realities. A review Agronomy Sust Developm. 2021;41:38. https://doi.org/10.1007/s13593-021-00689-w.
37. Bhandari M, Pal P, Brewer MJ. Future of Information Systems for Pest Management: Data Acquisition and Integration to Guiding Management Decisions. Arthropod Management and …. 2024;
38. Wani SP, Sudi R, Pardhasardhi G. Scaling-Up Land and Crop Management Solutions for Farmers Through Participatory Integrated Demonstrations "Seeing is Believing" Approach. In: Wani SP, Raju KV, Bhattacharyya T, editors. Scaling-up Solutions for Farmers: Technology, Partnerships and Convergence. Cham: Springer International Publishing; 2021. pp. 149–203. https://doi.org/10.1007/978-3-030-77935-1_4
39. Gul D, Banday RUZ. Transforming Crop Management Through Advanced AI and Machine Learning: Insights into Innovative Strategies for Sustainable Agriculture. ACRT. 2024;3. https://doi.org/10.5772/acrt.20240030
40. Jha MK, Peralta RC, Sahoo S. Simulation-Optimization for Conjunctive Water Resources Management and Optimal Crop Planning in Kushabhadra-Bhargavi River Delta of Eastern India. Int J Environ Res Public Health. 2020;17. https://doi.org/10.3390/ijerph17103521
41. Singh S, Jayaram R. Attainment of water and sanitation goals: a review and agenda for research. Sustain Water Resour Manag. 2022;8:146. https://doi.org/10.1007/s40899-022-00719-9.
42. Al-Gaadi KA, Hassaballa AA, Tola E, Kayad AG, Madugundu R, Alblewi B, et al. Prediction of potato crop yield using precision agriculture techniques. PLoS ONE. 2016;11: e0162219. https://doi.org/10.1371/journal.pone.0162219.
43. Bouguettaya A, Zarzour H, Kechida A, Taberkit AM. Deep learning techniques to classify agricultural crops through UAV imagery: a review. Neural Comput Appl. 2022;34:9511–36. https://doi.org/10.1007/s00521-022-07104-9.
44. Wu J, Vincent B, Yang J, Bouarfa S, Vidal A. Remote sensing monitoring of changes in soil salinity: a case study in Inner Mongolia, China. Sensors (Basel). 2008;8:7035–49. https://doi.org/10.3390/s8117035.
45. Rodriguez J, Ustin S, Sandoval-Solis S, O'Geen AT. Food, water, and fault lines: remote sensing opportunities for earthquake-response management of agricultural water. Sci Total Environ. 2016;565:1020–7. https://doi.org/10.1016/j.scitotenv.2016.05.146.
46. Kwon C-T, Heo J, Lemmon ZH, Capua Y, Hutton SF, Van Eck J, et al. Rapid customization of Solanaceae fruit crops for urban agriculture. Nat Biotechnol. 2020;38:182–8. https://doi.org/10.1038/s41587-019-0361-2.
47. Okoffo ED, Denkyirah EK, Adu DT, Fosu-Mensah BY. A double-hurdle model estimation of cocoa farmers' willingness to pay for crop insurance in Ghana. Springerplus. 2016;5:873. https://doi.org/10.1186/s40064-016-2561-2.
48. Abate T, van Huis A, Ampofo JK. Pest management strategies in traditional agriculture: an African perspective. Annu Rev Entomol. 2000;45:631–59. https://doi.org/10.1146/annurev.ento.45.1.631.
49. Donatelli M, Magarey RD, Bregaglio S, Willocquet L, Whish JPM, Savary S. Modelling the impacts of pests and diseases on agricultural systems. Agric Syst. 2017;155:213–24. https://doi.org/10.1016/j.agsy.2017.01.019.
50. Murrell EG. Can agricultural practices that mitigate or improve crop resilience to climate change also manage crop pests? Curr Opin Insect Sci. 2017;23:81–8. https://doi.org/10.1016/j.cois.2017.07.008.
51. Anderson JA, Ellsworth PC, Faria JC, Head GP, Owen MDK, Pilcher CD, et al. Genetically engineered crops: importance of diversified integrated pest management for agricultural sustainability. Front Bioeng Biotechnol. 2019;7:24. https://doi.org/10.3389/fbioe.2019.00024.
52. Bruce TJA. GM as a route for delivery of sustainable crop protection. J Exp Bot. 2012;63:537–41. https://doi.org/10.1093/jxb/err281.

53. Lysaght T, Lim HY, Xafis V, Ngiam KY. AI-assisted decision-making in healthcare: the application of an ethics framework for big data in health and research. Asian Bioethics Rev. 2019;11:299–314. https://doi.org/10.1007/s41649-019-00096-0.
54. Koski E, Murphy J. AI in healthcare. Stud Health Technol Inform. 2021;284:295–9. https://doi.org/10.3233/SHTI210726.
55 Swain J, VerMilyea MT, Meseguer M, Ezcurra D, Fertility AI Forum Group. AI in the treatment of fertility: key considerations. J Assist Reprod Genet. 2020;2020(37):2817–24. https://doi.org/10.1007/s10815-020-01950-z.
56. Zaffaroni M, Cunniffe NJ, Bevacqua D. An ecophysiological model of plant-pest interactions: the role of nutrient and water availability. J R Soc Interface. 2020;17:20200356. https://doi.org/10.1098/rsif.2020.0356.
57. Kim H. AI, big data, and robots for the evolution of biotechnology. Genomics Inform. 2019;17: e44. https://doi.org/10.5808/GI.2019.17.4.e44.
58. NsiahFrimpong B, Oppong A, Prempeh R, Appiah-Kubi Z, Abrokwah LA, Mochiah B, M, et al. Farmers' knowledge, attitudes and practices towards management of cassava pests and diseases in forest transition and Guinea savannah agro-ecological zones of Ghana. Gates Open Res. 2020;4:101. https://doi.org/10.12688/gatesopenres.13114.2.
59. Wenk EH, Falster DS. Quantifying and understanding reproductive allocation schedules in plants. Ecol Evol. 2015;5:5521–38. https://doi.org/10.1002/ece3.1802.
60. Jin H, Li M, Duan S, Fu M, Dong X, Liu B, et al. Optimization of light-harvesting pigment improves photosynthetic efficiency. Plant Physiol. 2016;172:1720–31. https://doi.org/10.1104/pp.16.00698.
61. Koshkin S, Zalles Z, Tobin MF, Toumbacaris N, Spiess C. Optimal allocation in annual plants with density-dependent fitness. Theory Biosci. 2021;140:177–96. https://doi.org/10.1007/s12064-021-00343-9.
62. Pearse IS, Rosenheim JA. Phylogenetic escape from pests reduces pesticides on some crop plants. Proc Natl Acad Sci USA. 2020;117:26849–53. https://doi.org/10.1073/pnas.2013751117.
63. Abd El-Ghany NM, Abd El-Aziz SE, Marei SS. A review: application of remote sensing as a promising strategy for insect pests and diseases management. Environ Sci Pollut Res Int. 2020;27:33503–15. https://doi.org/10.1007/s11356-020-09517-2.
64. Kumar R, Farooq M, Qureshi M. Advancing precision agriculture through artificial intelligenc. A biologists guide to artificial intelligence. Amsterdam: Elsevier; 2024. p. 151–65. https://doi.org/10.1016/B978-0-443-24001-0.00010-5.
65. Manavalan R. Automatic identification of diseases in grains crops through computational approaches: a review. Comput Electron Agric. 2020;178: 105802. https://doi.org/10.1016/j.compag.2020.105802.
66. Haridasan A, Thomas J, Raj ED. Deep learning system for paddy plant disease detection and classification. Environ Monit Assess. 2022;195:120. https://doi.org/10.1007/s10661-022-10656-x.
67. Jayasooriya G. Diagnosis of bacterial leaf blight, brown spots and leaf smut rice plant diseases. 2022.
68. Ali A, Hussain T, Tantashutikun N, Hussain N. Application of smart techniques, internet of things and data mining for resource use efficient and sustainable crop production. Agriculture. 2023.
69. Kanitkar A, Wadekar I. Digital agriculture: is this the future of'new. State of India's Livelihoods. 2023.
70. Shankar P, Werner N, Selinger S. Artificial intelligence driven crop protection optimization for sustainable agriculture. Piscataway: IEEE; 2020.
71. Balaska V, Adamidou Z, Vryzas Z, Gasteratos A. Sustainable crop protection via robotics and artificial intelligence solutions. Machines. 2023;11:774. https://doi.org/10.3390/machines11080774.
72. Voosen P. The AI detectives. Science. 2017;357:22–7. https://doi.org/10.1126/science.357.6346.22.
73. Schwendicke F, Mertens S, Cantu AG, Chaurasia A, Meyer-Lueckel H, Krois J. Cost-effectiveness of AI for caries detection: randomized trial. J Dent. 2022;119: 104080. https://doi.org/10.1016/j.jdent.2022.104080.
74. Le Cointe R, Simon TE, Delarue P, Hervé M, Leclerc M, Poggi S. Reducing the use of pesticides with site-specific application: the chemical control of Rhizoctonia Solani as a case of study for the management of soil-borne diseases. PLoS ONE. 2016;11: e0163221. https://doi.org/10.1371/journal.pone.0163221.
75. Kumar R, Farooq M, Qureshi M. Advancing precision agriculture through artificial intelligence: exploring the future of cultivation. Biologist s Guide to Artificial Intelligence. Cambridge: Academic Press; 2024.
76. Khan A, Malebary SJ, Dang LM, Binzagr F, Song H-K, Moon H. AI-enabled crop management framework for pest detection using visual sensor data. Plants. 2024. https://doi.org/10.3390/plants13050653.
77. Ngugi HN, Ezugwu AE, Akinyelu AA, Abualigah L. Revolutionizing crop disease detection with computational deep learning: a comprehensive review. Environ Monit Assess. 2024;196:302. https://doi.org/10.1007/s10661-024-12454-z.
78. Pandey DK, Mishra R. Towards sustainable agriculture: harnessing AI for global food security. Artif Intell Agric. 2024;12:72–84. https://doi.org/10.1016/j.aiia.2024.04.003.
79. Hachimi CE, Belaqziz S, Khabba S, Sebbar B, Dhiba D, Chehbouni A. Smart weather data management based on artificial intelligence and big data analytics for precision agriculture. Agriculture. 2022;13:95. https://doi.org/10.3390/agriculture13010095.
80. Chen L, Chen Z, Zhang Y, Liu Y, Osman AI, Farghali M, et al. Artificial intelligence-based solutions for climate change: a review. Environ Chem Lett. 2023. https://doi.org/10.1007/s10311-023-01617-y.
81. van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: a systematic literature review. Comput Electron Agric. 2020;177: 105709. https://doi.org/10.1016/j.compag.2020.105709.
82. Oyinbo O, Chamberlin J, Vanlauwe B, Vranken L, Kamara YA, Craufurd P, et al. Farmers' preferences for high-input agriculture supported by site-specific extension services: evidence from a choice experiment in Nigeria. Agric Syst. 2019;173:12–26. https://doi.org/10.1016/j.agsy.2019.02.003.
83. Khakbazan M, Moulin A, Huang J. Economic evaluation of variable rate nitrogen management of canola for zones based on historical yield maps and soil test recommendations. Sci Rep. 2021;11:4439. https://doi.org/10.1038/s41598-021-83917-3.
84. Sapkota TB, Jat ML, Rana DS, Khatri-Chhetri A, Jat HS, Bijarniya D, et al. Crop nutrient management using Nutrient Expert improves yield, increases farmers' income and reduces greenhouse gas emissions. Sci Rep. 2021;11:1564. https://doi.org/10.1038/s41598-020-79883-x.
85. Li S, Lei Y, Zhang Y, Liu J, Shi X, Jia H, et al. Rational trade-offs between yield increase and fertilizer inputs are essential for sustainable intensification: a case study in wheat-maize cropping systems in China. Sci Total Environ. 2019;679:328–36. https://doi.org/10.1016/j.scitotenv.2019.05.085.

86. Ren H, Han K, Liu Y, Zhao Y, Zhang L, He Q, et al. Improving smallholder farmers' maize yields and economic benefits under sustainable crop intensification in the North China Plain. Sci Total Environ. 2021;763: 143035. https://doi.org/10.1016/j.scitotenv.2020.143035.
87. Mehdi B, Lehner B, Ludwig R. Modelling crop land use change derived from influencing factors selected and ranked by farmers in North temperate agricultural regions. Sci Total Environ. 2018;631–632:407–20. https://doi.org/10.1016/j.scitotenv.2018.03.014.
88. Srinivasa Rao Madala VVRS. An advanced weed detection using deep learning techniques. NVEO—NATURAL VOLATILES & ESSENTIAL OILS Journal | NVEO. 2021.
89. Devarajan AK, Truu M, Gopalasubramaniam SK, Muthukrishanan G, Truu J. Application of data integration for rice bacterial strain selection by combining their osmotic stress response and plant growth-promoting traits. Front Microbiol. 2022;13:1058772. https://doi.org/10.3389/fmicb.2022.1058772.
90. Partel V, Charan Kakarla S, Ampatzidis Y. Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. Comput Electron Agric. 2019;157:339–50. https://doi.org/10.1016/j.compag.2018.12.048.
91. Vijayakumar V, Ampatzidis Y, Schueller JK, Burks T. Smart spraying technologies for precision weed management: a review. Smart Agric Technol. 2023;6:100337.
92. Machleb J, Peteinatos GG, Kollenda BL, Andújar D, Gerhards R. Sensor-based mechanical weed control: present state and prospects. Comput Electron Agric. 2020;176: 105638. https://doi.org/10.1016/j.compag.2020.105638.
93. Tobal A, Mokhtar SA. Weeds identification using evolutionary artificial intelligence algorithm. J Comput Sci. 2014;10:1355.
94. Zaman M, Kurepin LV, Catto W, Pharis RP. Enhancing crop yield with the use of N-based fertilizers co-applied with plant hormones or growth regulators. J Sci Food Agric. 2015;95:1777–85. https://doi.org/10.1002/jsfa.6938.
95. Nieto L, Schwalbert R, Prasad PVV, Olson BJSC, Ciampitti IA. An integrated approach of field, weather, and satellite data for monitoring maize phenology. Sci Rep. 2021;11:15711. https://doi.org/10.1038/s41598-021-95253-7.
96. Battula SK, Garg S, Naha RK, Thulasiraman P, Thulasiram R. A micro-level compensation-based cost model for resource allocation in a fog environment. Sensors (Basel). 2019. https://doi.org/10.3390/s19132954.
97. Shafiee-Jood M, Cai X. Reducing food loss and waste to enhance food security and environmental sustainability. Environ Sci Technol. 2016;50:8432–43. https://doi.org/10.1021/acs.est.6b01993.
98. Holzinger A, Saranti A, Angerschmid A, Retzlaff CO, Gronauer A, Pejakovic V, et al. Digital transformation in smart farm and forest operations needs human-centered AI: challenges and future directions. Sensors (Basel). 2022. https://doi.org/10.3390/s22083043.
99. Ghalehkhondabi I, Maihami R. Sustainable municipal solid waste disposal supply chain analysis under price-sensitive demand: a game theory approach. Waste Manag Res. 2020;38:300–11. https://doi.org/10.1177/0734242X19886650.
100. Bhat SA, Huang N-F, Sofi IB, Sultan M. Agriculture-food supply chain management based on blockchain and IoT: a narrative on enterprise blockchain interoperability. Agriculture. 2021;12:40. https://doi.org/10.3390/agriculture12010040.
101. Chen H-Y, Sharma K, Sharma C, Sharma S. Integrating explainable artificial intelligence and blockchain to smart agriculture: research prospects for decision making and improved security. Smart Agric Technol. 2023;6: 100350. https://doi.org/10.1016/j.atech.2023.100350.
102 Torky M, Hassanein AE. Integrating blockchain and the internet of things in precision agriculture: analysis, opportunities, and challenges. Comput Electron Agric. 2020. https://doi.org/10.1016/j.compag.2020.105476.
103. Dhanaraju M, Chenniappan P, Ramalingam K, Pazhanivelan S, Kaliaperumal R. Smart farming: internet of things (IoT)-based sustainable agriculture. Agriculture. 2022;12:1745. https://doi.org/10.3390/agriculture12101745.
104. Rejeb A, Abdollahi A, Rejeb K, Treiblmaier H. Drones in agriculture: a review and bibliometric analysis. Comput Electron Agric. 2022;198: 107017. https://doi.org/10.1016/j.compag.2022.107017.
105. Dey B, Abir KAM, Ahmed R, Salam MA, Redowan M, Miah MD, et al. Monitoring groundwater potential dynamics of north-eastern Bengal Basin in Bangladesh using AHP-Machine learning approaches. Ecol Indic. 2023;154: 110886. https://doi.org/10.1016/j.ecolind.2023.110886.
106. Delfani P, Thuraga V, Banerjee B, Chawade A. Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change. Precision Agric. 2024;25:2589–613. https://doi.org/10.1007/s11119-024-10164-7.
107. Malashin I, Tynchenko V, Gantimurov A, Nelyub V, Borodulin A, Tynchenko Y. Predicting sustainable crop yields: deep learning and explainable AI tools. Sustainability. 2024;16:9437. https://doi.org/10.3390/su16219437.
108. Neethirajan S, Scott S, Mancini C, Boivin X, Strand E. Human-computer interactions with farm animals-enhancing welfare through precision livestock farming and artificial intelligence. Front Vet Sci. 2024;11:1490851. https://doi.org/10.3389/fvets.2024.1490851.
109. Arshad MF, Burrai GP, Varcasia A, Sini MF, Ahmed F, Lai G, et al. The groundbreaking impact of digitalization and artificial intelligence in sheep farming. Res Vet Sci. 2024;170: 105197. https://doi.org/10.1016/j.rvsc.2024.105197.
110. Jiao S, Chen W, Wang J, Du N, Li Q, Wei G. Soil microbiomes with distinct assemblies through vertical soil profiles drive the cycling of multiple nutrients in reforested ecosystems. Microbiome. 2018;6:146. https://doi.org/10.1186/s40168-018-0526-0.
111. Zhao L, Walkowiak S, Fernando WGD. Artificial intelligence: a promising tool in exploring the phytomicrobiome in managing disease and promoting plant health. Plants. 2023. https://doi.org/10.3390/plants12091852.
112. Chauhan P, Sharma N, Tapwal A, Kumar A, Verma GS, Meena M, et al. Soil microbiome: diversity benefits and interactions with plants. Sustainability. 2023;15:14643. https://doi.org/10.3390/su151914643.
113. Wang X, Chi Y, Song S. Important soil microbiota's effects on plants and soils: a comprehensive 30-year systematic literature review. Front Microbiol. 2024;15:1347745. https://doi.org/10.3389/fmicb.2024.1347745.
114. Suman J, Rakshit A, Ogireddy SD, Singh S, Gupta C, Chandrakala J. Microbiome as a key player in sustainable agriculture and human health. Front Soil Sci. 2022. https://doi.org/10.3389/fsoil.2022.821589.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.