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Review

AI-Driven Future Farming: Achieving Climate-Smart and Sustainable Agriculture

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Abstract: Agriculture, an essential driver of economic expansion, is faced by the issue of sustaining an increasing global population in the context of climatic uncertainty and limited resources. As a result, "Smart Farming", which uses cutting-edge artificial intelligence (AI) to support autonomous decision-making, has become more popular. This article explores how the Internet of Things (IoT), AI, machine learning (ML), remote sensing, and variable-rate technology (VRT) work together to transform agriculture. Using sophisticated algorithms to predict soil conditions, improving agricultural yield projections, diagnosing water stress from sensor data, and identifying plant diseases and weeds through image recognition, crop mapping, and AI-guided crop selection are some of the main applications investigated. Furthermore, the precision with which VRT applies water, pesticides, and fertilizers optimizes resource utilization, enhancing sustainability and efficiency. To effectively meet the world's food demands, this study forecasts a sustainable agricultural future that combines AI-driven approaches with conventional methods.

Keywords: climate smart; artificial intelligence (AI); machine learning (ML); internet of things (IoT); variable-rate technology (VRT)

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1. Introduction

The rapid growth of the global population, predicted to reach 9.7 billion by 2050, poses substantial challenges for the agricultural sector, mostly in terms of sustainability and efficiency [1]. Agriculture has faced increasing challenges in recent years because of the rising impacts of climate change [2]. Changes in weather patterns, greater variability, and the advent of new pests and diseases have markedly heightened the vulnerability of conventional farming systems [3]. Integrating advanced technologies like intelligent automation, predictive algorithms, and connected devices into farming practices offers promising solutions, enabling the transition to more sustainable and productive approaches. This article discusses the complete use of these modern technologies to revolutionize agriculture, enhancing productivity and sustainability through precision farming and smart agriculture initiatives. Traditional agricultural practices, while successful in the past, now face limitations due to increased environmental and economic pressures. Sustainable agriculture emerges as a crucial approach, advocating for the preservation of environmental quality, the enhancement of soil fertility, water conservation, and biodiversity protection. This form of agriculture is not just about altering techniques, but about transforming the entire food system to be sustainable in the long term [4]. The incorporation of automation and smart devices in agriculture provides a promising path toward achieving these goals. These advanced and efficient techniques are commonly referred to as precision or smart farming. Precision agriculture represents a significant shift from traditional farming methods. It integrates advanced technologies to create a more precise and controlled form of agriculture that conservatively uses resources like water, nutrients, and pesticides, hence decreasing costs and environmental impacts [5]. These technologies, including AI and IoT, provide farmers with data-driven insights that help optimize farming operations by predicting weather conditions, analyzing soil health, and monitoring crop health in real time. Fundamental technologies in precision agriculture include the Global Positioning System (GPS) and Geographic Information Systems (GISs), which allow for accurate agricultural mapping and management. These technologies help in managing spatial variability within fields, which can be caused by multiple factors, including soil composition, moisture levels, and historical crop performance [6]. Yield monitors and variable-rate technology (VRT) allow for the detailed monitoring and responsive application of inputs like fertilizers, pesticides, and water. This is essential for reducing waste and its negative effects on the environment, in addition to improving resource usage efficiency [7]. AI and ML are at the early stage of transforming agriculture into a more data-driven and predictive domain. These technologies analyze huge amounts of data from satellite images, sensors, and IoT devices to provide insights into crop health, predict yields, and optimize the distribution of resources. Historically, the use of data in agriculture started in the 1990s with soil and yield maps. This evolved into precise management practices, utilizing grid sampling techniques to optimize soil fertility and pH levels [8]. By 2010, automation and large-scale farm equipment integrated with GPS and autosteer technologies became widespread. These advancements reduced operational burdens and enhanced data collection capabilities [9]. Around 2012, "Decision Agriculture" emerged, introducing internet-connected tractors and harvesters. These innovations enabled real-time data analysis to optimize agricultural operations [10]. During this period, digital tools and big data platforms gained popularity. They allowed seamless data integration and analysis, improving decision-making in farm management. The application of machine learning models illustrates the advanced capabilities of modern agriculture. These models analyze data to predict pest attacks and diseases, enabling farmers to take preventive measures in advance [11]. Additionally, IoT technology plays a crucial role in precision agriculture. It connects various sensors across fields to continuously monitor moisture, pH levels, temperature, and crop health. This robust sensor network continuously collects data and sends it to centralize systems for processing and analysis, enabling agricultural management to make well-informed decisions [12]. Furthermore, IoT applications include smart irrigation systems that accurately dispense water exactly when and where it is needed, significantly preserving water resources and enhancing sustainability [13]. Beyond sensor technology, modern farm machinery incorporates modems that are integrated with the internet, embedded within the larger framework of the Industrial Internet. This connectivity spans various aspects of agriculture, transforming farms into interconnected, data-driven environments. The application of this extensive data collection, while not new, is revolutionizing global agricultural operations, shifting the paradigms of farming practices. Moreover, agricultural decision-making is supported by advanced data mining and management tools. Crop modeling simulations, which include data from different sources such as soil and weather conditions, along with management practices like fertilization, assist in estimating potential yields. These models are highly valuable for farmers, particularly when integrated with weather prediction models. These models use extensive datasets to accurately forecast weather patterns and precipitation. Such forecasts are important in planning the deployment of farm equipment and labor [14]. The trend of large data in agriculture unfolds through a structured four-part process that enhances both learning and practical application. Farmers first upload data gathered from various sources, such as drones, machines, and ground sensors. The data are then combined by Agricultural Technology Providers (ATPs), enhanced with other essential datasets, and applied with complex algorithms for detailed analysis. Subsequently, ATPs deliver tailored solutions and recommendations based on these analyses. Armed with these insights, farmers can make strategic decisions to optimize the agronomic, economic, and management aspects of their operations [15]. Despite these technological advances, the broader adoption of recently developed technology in agriculture faces several substantial barriers. Significant challenges must be addressed to fully harness the potential of these innovations. These include the high costs of the technologies, the need for extensive farmer training, concerns about data security, and the requirement for a robust technological infrastructure to support AI and IoT integration into daily farming practices [16]. Achieving these goals requires not only technological advances, but also supportive policies and infrastructure investments to ensure all farmers benefit from these innovations [17]. The continued advancement of these tools holds the potential to address pressing global challenges like food security, sustainable practices, and climate resilience. As technology develops, it might help solve important global issues, including worldwide warming, sustainability, and food security. However, the successful implementation of these technologies will depend on collaborative efforts between governments, technology providers, and the farming community to ensure the global implementation of the advantages of technology-driven agriculture. This paper provides a comprehensive examination of the integration of advanced technologies in agriculture, beginning with an exploration of the historical evolution of farming practices and the initial adoption of technological innovations. It highlights the transformative role of remote sensing data, detailing satellite-based technologies, image preprocessing techniques, and the application of spectral indices in areas such as pest and disease prediction, soil health analysis, resource optimization, and automation. The discussion extends to modern applications of artificial intelligence, machine learning, and deep learning, emphasizing their contributions to predictive analytics, crop modeling, stress detection, and intelligent harvesting. Additionally, the pivotal roles of the Internet of Things in precision agriculture and variable-rate technology in smart farming are analyzed to illustrate their potential to enhance efficiency and sustainability. This paper concludes by addressing the opportunities and challenges associated with these advancements, offering insights into the future of climate-smart and sustainable agriculture.

2. Methods and Results

2.1. The Evolution of Agriculture and Technology

There have been four major phases in the development of agricultural technology. Beginning around 10,000 BC, agriculture 1.0 relied on manual labor, animal power, and simple equipment, which resulted in ineffective operations with low productivity. The 19th-century emergence of agriculture 2.0 included mechanical equipment like harvesters and tractors, as well as chemical inputs, which increased productivity but had drawbacks due to poor resource usage. Through automation, robots, and computer-based systems, agriculture 3.0 improved farming throughout the 20th and 21st centuries. However, the comparatively low intelligence of these technologies resulted in limited precision. To improve resource management and decision-making, agriculture 4.0 now emphasizes smart devices and systems that integrate technology like drones, the Internet of Things, and AI-driven analytics. However, this modern phase introduces additional concerns, particularly in terms of data security and privacy. This timeline highlights the evolution of agricultural methods, demonstrating the ongoing transition to intelligent and automated solutions while addressing the inefficiencies and difficulties of each stage (Figure 1).

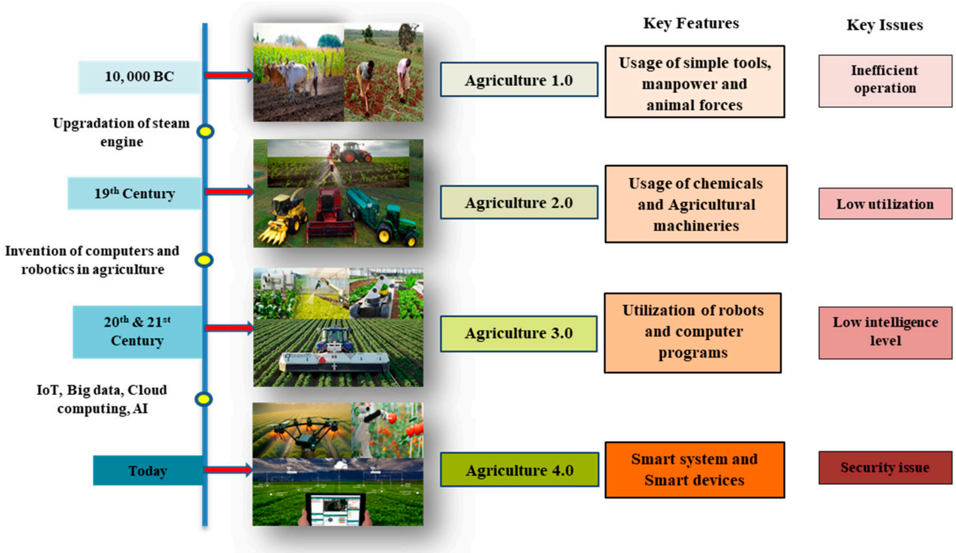


Figure 1. Upgradation of agriculture.

2.1.1. Traditional Farming Practices

Traditional farming practices have been the backbone of agriculture for centuries, focusing primarily on manual labor and rudimentary tools to cultivate crops and rear livestock. To maintain soil fertility, these practices relied on natural resources like rainfall, organic manure, and crop rotation techniques. Techniques such as plowing, sowing, weeding, and harvesting were predominantly performed manually or with the aid of animals. This reliance on physical labor and organic inputs, while effective in past eras, limits scalability and efficiency, which are critical in today's context of increasing population and food demand.

2.1.2. Early Applications of Technology in Agriculture

The initial integration of technology in agriculture began with the mechanization of basic tasks such as plowing and threshing at the beginning of 20th century. The emergence of tractors and combine harvesters dramatically increased the scale and speed of these operations, leading to significant gains in productivity. Synthetic pesticides and fertilizers were developed in later decades, which increased yields even more while additionally highlighting questions about the sustainability of the environment. During the 1970s and 1980s, the development of hydroponics and controlled environment agriculture began to show how technology could not only increase productivity, but also conserve resources.

2.1.3. The Shift Towards DATA-Driven Agriculture

In the late 20th and early 21st centuries, however, data-driven agriculture emerged, marking the beginning of a true revolution. GIS and GPS technologies were introduced at this time, enabling the fine-grained mapping and analysis of farms. The current concept of precision agriculture was made possible in large part by this skill. Information technology and a variety of tools, including sensors, drones, and internet platforms, are used in precision farming to track and improve crop growth and soil health. Data-driven agriculture combines these technologies to create detailed maps of field variability, allowing for the precise application of agricultural inputs, thereby reducing waste and increasing efficiency. To manage essential natural resources effectively, precision agriculture (PA) and environmental responsibility are critical components of modern agriculture. The "five Rs" principle within PA emphasizes appropriate inputs, optimal timing, correct placement, adequate quantity, and proper application methods, known as site-specific management. This approach addresses the challenges of traditional agricultural systems exacerbated by global market competition. Precision agriculture operates on extensive datasets derived from various sources to thoroughly analyze soil conditions, crop health, and field environments, making it a data-intensive field, as shown in Figure 2. For instance, soil sensors can detect moisture and nutrient levels, adjusting irrigation and fertilization in real time. Yield monitors on harvesters can assess crop performance across different sections of a field, which helps in fine-tuning planting strategies and input levels for subsequent seasons.

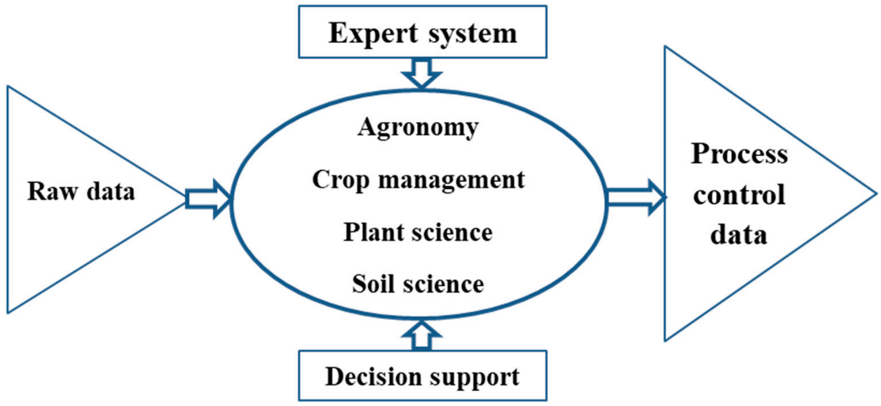


Figure 2. Information flow in precision agriculture.

2.2. Remote Sensing Data

2.2.1. Satellites

The process of measuring reflected and emitted radiation from a distance, usually using satellites, to identify and track the location of physical features is known as remote sensing. This procedure requires gathering information at different electromagnetic spectrum frequencies. The launch of the Advanced Very-High-quality Radiometer meteorological satellite for weather analysis in the late 1960s was a significant breakthrough in remote sensing. In the early 1970s, the Landsat program was initiated for natural resource monitoring and mapping. Progress in rocket technology and sensor design has resulted in the availability of a wide variety of satellite data. These advancements in spatial and spectral resolutions have expanded the applications of remote sensing and enabled precise environmental monitoring and digital image analysis. However, Landsat and Sentinel satellites play important roles in agricultural monitoring and management by providing comprehensive and free Earth observation data [18,19]. Since 1972, NASA and the USGS have operated the Landsat series (Landsat 1 to 9), which provide multispectral images with a modest spatial resolution of 30 m and a 16-day return cycle. Each scene covers an area of 185 km $\times$ 180 km (https://www.usgs.gov/ (accessed on 24 December 2024)). In addition, the Sentinel satellites, part of the European Union's Copernicus program, provide high-resolution data from 23 June 2015 with frequent updates (https://www.esa.int/Applications/Observing_the_Earth/Copernicus/The_Sentinel_missions (accessed on 24 December 2024)). The Sentinel-2 satellite offers high-frequency Earth observation with a revisit time of roughly 5 days, enabling comprehensive surface monitoring [ESA, 2015]. Sentinel-2 is particularly well suited for precise land cover categorization, vegetation study, and other applications that demand fine spatial precision because of its 13 spectral bands that cover a broad range of the electromagnetic spectrum and its spatial resolution of 10 to 60 m [20].

2.2.2. Image Pre-Processing

Geometric and radiometric corrections are essential processes for enhancing the accuracy and quality of satellite imagery. All satellite images are georeferenced to correct geometric distortions, employing control points using the global positioning system (GPS).

Additionally, radiometric corrections are applied to reduce noise introduced by sensors, processing, and atmospheric conditions. This process begins with converting the raw digital number DN(λ) values of the images to radiance, as described by the following equation [21–23]:

$$L(\lambda) = \text{Grain}\ (\lambda) + \text{DN}\ (\lambda) + \text{Offset}\ (\lambda) \tag{1}$$

Here, λ stands for wavelength (μm), Grain (λ) for band-specific rescaling gain factor [(W/m^2 sr μm)/DN], Offset (λ) for band-specific rescaling offset [W/(m^2 μm sr), and L (λ) for radiance [W/(m^2 μm sr]. The following equation was then used to calculate the reflectance at the surface (ρ (λ)).

$$\rho\ (\lambda) = (((L\ (\lambda) - (L\ (DP, \lambda)) \times D\hat{}2 \times \pi)/(E\ (\lambda) \times \cos(\theta)) \tag{2}$$

ρ (λ) is the spectral reflectance at the surface (unitless), L (DP, λ) shows the spectral radiance acquired from a dark object [W/(m^2 μm sr)], D represents Earth-to-sun distance (astronomic units), π is the mathematical constant 3.14159, E (λ) represents mean exo-atmospheric solar irradiance [W/(m^2 μm)], and θ shows solar zenith angle (degrees).

2.2.3. Spectral Indices in the Literature

Spectral indices are specific combinations of spectral bands used to detect and quantify various surface properties. Researchers have developed several spectral indices to assess environmental parameters, including vegetation health, salt concentration, and soil characteristics. Each index highlights particular features, enhancing the accuracy of remote sensing in environmental monitoring. Table 1 provides a comprehensive summary of the important spectral indices outlined in the scientific literature.

Table 1. Commonly used spectral indices in the literature.

Types	Indices	Formula	References
Vegetation Indices	NDVI	$(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R)$	[24]
	SAVI	$2(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R + 1)$	[25]
	VSSI	$2\rho_G - 5(\rho_R + \rho_{NIR})$	[26]
	EVI	$2.5(\rho_{NIR} - \rho_R)/(\rho_{NIR} + 6\rho_R + 7.5\rho_B + 1)$	[27]
	NLVI	$(\rho_{NIR}{}^2 - \rho_R)/(\rho_{NIR}{}^2 + \rho_R)$	[28]
	DVI	$\rho_{NIR} - \rho_R$	[29]
	GRVI	ρ_{NIR}/ρ_G	[30]
Salinity Indices	SIT	$(\rho_R/\rho_{NIR})100$	[31]
	SI	$(\rho_B \times \rho_R)^{0.5}$	[32]
	SI (1)	$(\rho_G \times \rho_R)^{0.5}$	[33]
	SI (2)	$(\rho_G{}^2 + \rho_R{}^2 + \rho_{NIR}{}^2)^{0.5}$	[34]
	SI (3)	$(\rho_G{}^2 + \rho_{NIR}{}^2)^{0.5}$	[35]
	SI (4)	ρ_{SWIR1}/ρ_{NIR}	[32]
	SI (7)	$((\rho_{NIR} \times \rho_R) - (\rho_{SWIR1}{}^{0.5} - \rho_{SWIR2}{}^{0.5}))/((\rho_B{}^2 \times \rho_G{}^2) + (\rho_{SWIR1}{}^{0.5} - \rho_{SWIR2}{}^{0.5}))$	[23]
	SI (I)	ρ_B/ρ_R	[36]
	SI (II)	$(\rho_B - \rho_R)/(\rho_B + \rho_R)$	[36]
	SI (III)	$\rho_G \times \rho_R/\rho_B$	[36]
	SI (IV)	$\rho_R \times \rho_{NIR}/\rho_G$	[36]
	SI (IV)	$\rho_B \times \rho_R/\rho_G$	[36]
	ESRI	$\rho_G{}^2/\rho_B \times \rho_{SWIR1}$	[37]
	CRSI	$((\rho_{NIR} \times \rho_R - \rho_G \times \rho_B)/(\rho_{NIR} \times \rho_R + \rho_G \times \rho_B))^{0.5}$	[38]
Soil Indices	CI	$\rho_{SWIR1}/\rho_{SWIR2}$	[39]
	GI	$(\rho_{SWIR1} - \rho_{SWIR2})/(\rho_{SWIR1} + \rho_{SWIR2})$	[40]
	BI	$(\rho_G{}^2 + \rho_B{}^2)^{0.5}$	[31]
	NMDI	$\rho_{NIR} - (\rho_{SWIR1} - \rho_{SWIR2})/\rho_{NIR} + (\rho_{SWIR1} - \rho_{SWIR2})$	[41]

NDVI: Normalized difference vegetation index; SAVI: Soil-adjusted vegetation index; VSSI: Vegetation soil salinity index; EVI: Enhanced vegetation index; NLVI: Non-linear vegetation index, DVI: Differential vegetation index; GRVI: Green ratio vegetation index; SI: Salinity index; ERSI: Enhanced residues soil salinity index; CRSI: Canopy response salinity index; CI: Clay index; GI: Gypsum index; BI: Brightness index; NMDI: Normalized multi-band drought index.

2.2.4. Remote Sensing Applications for Improving Agriculture Practices

Remote sensing systems play a vital role in PA applications. For instance, Sadeghi et al. [42] applied Sentinel-2 and Landsat-8 data to improve water resource management. In a related study, they studied the use of Landsat 8 images to monitor spatiotemporal vegetation responses to drought conditions. Remote sensing has also been employed for disease and pest monitoring. In this way, Sahabiev et al. [43] used information from Sentinel-2 and Landsat-8 data to predict agrochemical properties. Moreover, remote sensing data are mostly used to monitor crop development and yield in the precision agriculture field [44,45]. Recently, Mirzaee and Nafchi [46] introduced an innovative methodology to assess the nitrogen needs of crops. This approach utilized Sentinel-2 data to monitor and detect crop responses to applied nitrogen. The methodology showed a high performance by integrating Nitrogen-Rich Biosensor Spots (NRBSs) and remote sensing data. This methodology has the potential to enhance crop yields, optimize nitrogen inputs, and reduce environmental impacts.

2.3. Application of Technologies in Modern Agriculture

2.3.1. AI Applications for Predictive Analytics and Decision-Making

Artificial Intelligence (AI) in agriculture represents a transformative shift towards more data-driven methodologies that enhance productivity and sustainability. By analyzing data from farm operations and environmental conditions, intelligent systems provide predictive insights and support automated decision-making. This technology helps in the optimization of numerous agricultural operations, including planting, irrigation, harvesting, and pest management. Table 2 lists the cutting-edge technologies used in modern farming, along with their uses, limitations, and challenges.

Table 2. Summary of advanced technologies used in modern agriculture.

S. No	Technology	Applications	Limitations and Challenges	References
1.	Artificial intelligence (AI)	• Predictive crop modeling • Pest and disease prediction • Soil health analysis • Automated machinery	✓ Limitations in real-time dataset availability ✓ Absence of dataset standards ✓ Capturing data at close range ✓ Recognizing small symptoms ✓ Differences in image quality and lighting ✓ Disease development and similarities across classes ✓ Computational difficulties with big datasets ✓ Combining multimodal data	[47–50]
2.	Deep learning (DL) and machine learning (ML) models	• Crop yield prediction • Disease and pest detection • Weed identification and management • Precision irrigation management • Nutrient management • Crop variety selection • Intelligent harvesting and optimization:	✓ Model failures are caused by small datasets; varied, real-world field images are crucial ✓ Accuracy and runtime are impacted by the size and type of input (e.g., background removal, vegetation indices) ✓ Costly, time-consuming, and specialized; unsupervised techniques require investigation ✓ Accuracy and inference time are traded off; site-specific datasets require retraining ✓ High processing overhead and reliance on hyperparameter adjustment ✓ Lightweight models and edge devices are attractive alternatives to models, which are frequently impractical ✓ Farmer knowledge is required; automation may be possible with IoT and reinforcement learning	[51,52]

Table 2. *Cont.*

S. No	Technology	Applications	Limitations and Challenges	References
3.	Internet of thing (IoT)	• Irrigation monitoring and control • Soil monitoring • Temperature and humidity monitoring • Animal monitoring and tracking • Water monitoring and controlling disease monitoring • Air monitoring • Fertilization monitoring	✓ The gathering, storing, processing, and transfer of data pose security threats to IoT-based agriculture ✓ Signal jamming causes inefficiencies and economic losses by interfering with communication, GPS, and remote monitoring ✓ Decision-making, accuracy, and data dependability are all harmed by node capture and outages ✓ Attacks on data transmission lead to surveillance, theft, or poor farming decisions ✓ For prevention, strong procedures like encryption, authentication, monitoring, and system updates are important	[53,54]
4.	Variable-rate technology (VRT): map-based and sensor-based techniques	• Variable-rate fertilization • Variable-rate seeding • Variable-rate irrigation:	✓ High prices, small farm sizes, technological constraints, insufficient technical assistance, and a lack of training are some of the obstacles to VRT adoption ✓ Younger farmers are more likely than older farmers to use VRTs, and adoption decisions are based on farm economics; farmers place a higher priority on profitability ✓ While higher non-farm income boosts VRT purchases, adoption is slowed by financial limitations, profit uncertainty, and expensive starting expenditures	[55]

▪ Predictive crop modeling

Intelligent algorithms combine real-time environmental factors and historical data to estimate crop yields, growth patterns, and the optimal periods for seeding and harvest. These models benefit farmers by making informed choices by predicting market needs and weather circumstances. With the use of advanced algorithms like neural networks, decision trees, and support vector machines, contemporary predictive crop models analyze a wide range of data sources, such as weather, soil conditions, crop types, and historical yield data (Figure 3). The explained models' performance assessment parameters and their descriptions are listed in Table 3.

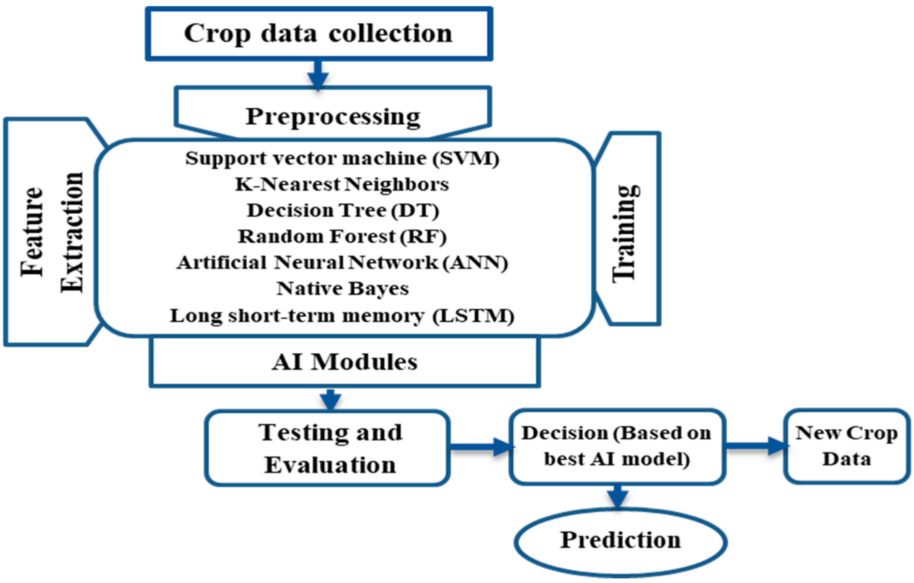


Figure 3. AI-based crop analysis and prediction.

Table 3. Performance assessment mathematical parameters of AI models and their descriptions.

Model	Performance Analysis Parameter	Description	References
Support Vector Machine (SVM)	Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$ where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives	SVM finds the hyperplane that maximizes the margin between classes. It uses hinge loss to discard the incorrect classifications.	[56]
K-Nearest Neighbors (KNN)	$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total predictions}}$	KNN uses its neighbors' approval rating to classify a data point. Performance is strongly impacted by KNN selection.	[57]
Decision Tree (DT)	$\text{Gini Index} = 1 - \sum_{i}^{C} p^2$ where p is the proportion of samples belonging to class i	To reduce the impurity (such as Gini or entropy), decision trees divide data according to feature thresholds	[58]
Random Forest (RF)	$\text{Accuracy} = \frac{1}{T}\sum_{i=1}^{T} Accuracy_t$ where T is the number of trees	Random Forest combines predictions using an ensemble of decision trees to increase prediction accuracy and decrease overfitting	[59]
Artificial Neural Network (ANN)	$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total predictions}}$	An ANN uses layers of neurons to map inputs to outputs, optimizing weights by backpropagation with a differentiable loss function, such as cross-entropy	[60]
Naïve Bayes	Posterior Probability, P(y|X) = P(X)P(X|y)P(y) P(yi|Xi): Posterior probability of the i-th data point being in class yi	Naïve Bayes models eliminate complicated joint probability computations; they simplify calculations and are especially useful when the independence condition is roughly valid	[61]
Long Short-Term Memory (LSTM)	MSE = $\frac{1}{N}\sum_{i=1}^{N}(yi - \hat{y}i)^2$ N: Total number of observations in the dataset. i: Index for individual data points. yi: True label. $\hat{y}i$: Predicted value	Temporal dependencies in sequential data are captured by LSTM, a recurrent neural network that utilizes gates (forget, input, and output)	[62]

These models not only forecast expected yields, but also suggest optimal planting and harvesting dates based on local soil and climatic conditions. Notable developments in this discipline are highlighted by in the literature. For instance, Kheir et al. [63] showed that convolutional neural networks were significantly more accurate than conventional techniques for predicting wheat yields in the Midwestern United States. Another example by Griffin et al. [64] showed that using ensemble learning to combine multiple predictive models could increase the reliability of predictions across varying environmental conditions. However, predictive crop models face several challenges that can impact their accuracy and deployment. The quality and volume of available data are crucial; data deficiencies, particularly in underdeveloped agricultural regions, pose significant obstacles. Additionally, these models require regular updates and calibration to stay effective amidst changing climatic conditions and agricultural practices [65].

Predictive crop modeling is expected to evolve with the integration of more detailed environmental data and the enhanced interpretability of AI models. The future may see the incorporation of high-resolution satellite imagery and advanced sensors to gather detailed soil and microclimate data. There is also an increasing interest in developing hybrid models that combine AI with traditional agronomic knowledge to improve decision-making processes [66,67].

- Pest and disease prediction

Intelligent systems enable advanced agricultural practices by identifying and removing weeds, predicting plant disease symptoms, and recommending effective pest management strategies. They help with irrigation scheduling, fertilizer delivery timing, and anticipating the best combinations of agronomic inputs. These technologies can also anticipate the optimal time for harvesting and automate the process [68]. Predictive analytics has the potential to completely transform the agriculture sector, with more data being collected and analyzed than ever before. Price predictions, market demand analysis, and optimal planting and harvesting schedules are just a few of the major issues that can be tackled using smart tools [69]. Smart technologies also assist in sorting produce by ripeness levels before they reach the market, improving quality control. Advanced field management leverages high-resolution imagery from drones and aerial devices for real-time predictions, helping create field and feed maps that indicate where crops need adjustments in pesticide, fertilizer, or water application. Cognitive systems provide valuable insights into seed selection, weather forecasts, soil conditions, and pest activity tailored to each location, enhancing farming precision [70].

- Soil health analysis

In agriculture, intelligent systems substantially improve soil health assessments by utilizing data from several sources, such as satellite imaging, drones, and sensors buried in the ground. To find nutritional shortfalls and soil flaws, these technologies analyze a variety of data, such as temperature, moisture content, nutrient content, soil conditions, and crop performance. This enables customized irrigation and fertilization plans that enhance crop health and fertility while directing exact soil management techniques. By modifying treatments in response to real-time pest activity, machine learning algorithms significantly contribute to the optimization of resource utilization, including that of pesticides and herbicides, hence improving sustainability and productivity. These systems also forecast how global disasters and environmental changes will affect agriculture, facilitating efficient resource management and crisis response. In addition to streamlining farming operations, this all-encompassing strategy supports long-term sustainability objectives [71–74].

- Resource optimization

To recognize patterns of excessive use and suggest optimization techniques, intelligent systems examine data on resource allocation and consumption. Preventive measures, such as keeping an eye on animal health and equipment performance, lower the cost of veterinarian care and equipment maintenance. Profitability naturally rises as these technologies reduce expenses across agricultural businesses and boost yields without requiring more resources. The goal of sustainable agriculture is to find an approach to meet the world's food and textile requirements without depleting available resources or leaving nothing for future generations. By leveraging intelligent systems, farmers can identify sustainable resource usage strategies to prevent water shortages and soil damage. With its various subfields and applications, AI offers agricultural solutions through programs and algorithms of varying complexity [75,76].

- Automated machinery

A promising solution to the labor shortage in agriculture may be the implementation of intelligent systems, autonomous tractors, and IoT. Because these technologies increase accuracy and decrease errors, they can also save expenses. At the intersection of these systems, including self-driving tractors, is precision farming. Furthermore, robots are a rapidly growing form of technology that can handle labor-intensive jobs like cutting lettuce and harvesting fruits and vegetables. Farmworkers have several advantages over robots. They may operate for longer periods of time, are less prone to errors, and are more accurate. Despite being data-rich, agriculture is difficult to analyze because of the complexity of the real world. Innovations in AI have the power to completely change the market by offering predictive analytics and deep data insights. Staying aware of the most recent developments in their sector may be very challenging for any organization. AI will speed up and improve the decision-making process for enterprises. Combining data and machine learning approaches can help organizations make better predictions and navigate a complex world.

2.3.2. Enhancing Agricultural Efficiency with ML and DL Models

Deep learning and machine learning are subfields of artificial intelligence that focus on developing systems that can recognize patterns, learn from data, and form opinions with minimal human intervention. ML processes data, learns from it, and makes decisions based on algorithms. Deep learning, which draws inspiration from neural networks found in the brain, excels at processing massive amounts of data. Through image recognition technologies, it is frequently used to identify trends and abnormalities in crop development, forecast insect outbreaks, and identify plant illnesses.

- Soil properties and weather prediction

Predicting soil properties is crucial in agriculture as it influences numerous decisions, including crop selection, land preparation, and fertilizer application. Since these characteristics are closely related to the local climate and geography, it is essential to accurately estimate them in order to implement efficient agricultural methods. Human activities notably impact soil quality, affecting the ability to cultivate crops efficiently [77]. Soil health is determined by several essential nutrients, listed as 17 key elements that are crucial for plant growth [78]. Electric and electromagnetic sensors are the main tools used to measure the availability of these nutrients, which helps farmers make well-informed decisions about the best crop production practices based on the unique nutritional profile of their soil. An Extreme Learning Machine (ELM)-based regression model was used in a noteworthy work [79] to forecast soil surface humidity. Using polarimetric Radarsat-2 data that had been pre-processed using the SNAP toolkit, this investigation was carried out on two terrains at Dicle University. When evaluated with several kernel functions, the ELM model showed excellent accuracy, especially when using the 'sine' kernel, which had the lowest root mean square error (RMSE) at 2.19%. Chowdary et al. [80] used soft sensors based on ELM to evaluate the composition of nutrient solutions in the context of soilless agriculture, which is becoming more and more popular as an innovative agricultural technique. This approach is critical, as the performance of soilless cultivation heavily relies on accurately monitoring variables like pH, temperature, and nutrient concentrations. The study achieved commendable RMSE values for predictions of sulfate and phosphate concentrations in nutrient solutions. Park et al. [81] used machine learning methods to improve soil moisture prediction with MODIS satellite data. By using a combination of Random Forest (RF) and Cubist algorithms, they increased soil moisture data accuracy, outperforming conventional statistical techniques. This method demonstrated a high coefficient of determination (R2) of 0.96 and an RMSE of 0.06, significantly better than results from ordinary least squares techniques. Reda et al. [82] utilized machine learning to estimate soil organic carbon (SOC) and total nitrogen (TN) in Moroccan agricultural lands using near-infrared spectroscopy, a method quicker and less resource-intensive than traditional chemical analyses. The ensemble learning models used in this study showed superior performance, with an R2 of 0.96 for SOC, underscoring the effectiveness of ML in predicting essential soil properties. Morellos et al. [83] further showed how well machine learning predicts soil characteristics using visible and infrared spectroscopy. The Least Square Support Vector Machine (LS-SVM) and Cubist algorithms performed better in their investigation than conventional multivariate techniques, providing accurate SOC, TN, and moisture content predictions. Using information from portable X-ray fluorescence (pXRF) spectrometry, Andrade et al. [84] investigated many machine learning models to forecast soil characteristics. According to their research, the most accurate forecasts for TN, soil organic matter, and cation exchange capacity were made using RF algorithms. Deiss et al. [85] demonstrated that tuning support vector machines (SVMs) for soil property predictions using mid-infrared spectroscopy data could lead to significant improvements in accuracy across multiple soil parameters, such as clay, sand, pH, and SOC. Finally, addressing the vital aspect of soil moisture, Stamenkovic et al. [86] and Song et al. [87] used machine learning algorithms to reliably forecast moisture content from hyperspectral pictures that were detected remotely. These models, including support vector regression and deep learning-based cellular automata, showcased high performance, offering practical solutions for precise irrigation scheduling. Together, these studies highlight how machine learning and deep learning technologies are revolutionizing agricultural soil property monitoring and prediction, enabling more productive and sustainable farming methods.

- Crop yield prediction

Farmers must estimate crop yields in order to boost agricultural output and efficiency. Weather patterns (temperature, humidity, rainfall, and sunlight hours), fertilizers, soil type and quality, pH level, and harvesting plans are some of the variables that affect crop yield [88]. This procedure emphasizes the significance of early anomaly identification to minimize large yield losses; the process takes the form of a feedback control system in which corrective measures are implemented upon identifying setbacks in crop growth. Advanced ML algorithms have been pivotal in enhancing crop yield predictions. For instance, Peng et al. [89] utilized Solar-Induced Chlorophyll Fluorescence (SIF) data from remote-sensed satellites to train ML models (SVM, ANN, RF) to predict maize and soybean yields in the U.S. Midwest. Their findings demonstrated the superiority of these non-linear algorithms over LASSO and ridge regression in terms of prediction accuracy. Similarly, Khaki et al. [90] employed deep neural networks (DNN) to predict hybrid maize yield across various locations between 2008 and 2016 in the United States and Canada, achieving a low RMSE and highlighting the impact of genotype, weather, and soil properties on yield accuracy. Environmental variables have a big impact on how accurate crop output forecasts are, as demonstrated by simulation results from various studies. In regions like Africa, where field data are limited, remotely sensed datasets are crucial for monitoring and predicting agricultural outputs. Cai Yaping et al. [91] used satellite and climate data to predict Australia's wheat yields, showing that climate data provide unique insights compared to satellite data, with an R^2 around 0.75. The timing of crop planting is another critical factor affecting productivity and financial outcomes. Gumuscu et al. [92] examined how well ML algorithms (kNN, SVM, and decision trees) predicted the best times to plant wheat in Turkey using climatic data and feature selection using genetic algorithms. Their study indicated that kNN algorithms robustly predict wheat planting dates. Deep learning techniques are also being applied to yield prediction in other crops. Nevavuori et al. [93] used a CNN trained on NDVI and RGB datasets from UAV-mounted cameras for wheat and barley yield estimation in Finland, with the RGB dataset yielding the most accurate results. In the context of fruit production, Koirala et al. [94] reviewed the application of CNNs for fruit detection and yield estimation, highlighting the utility of CNNs in extracting useful features from images for object detection and yield prediction. Kuwata et al. [95] applied DL models, specifically support vector regression (SVR), to estimate corn yields in Illinois using a combination of 5-year moving averages of corn crop yields, enhanced vegetation indices from MODIS satellite data, and historical climate data. Their model demonstrated a substantial correlation coefficient and RMSE, validated through 10-fold cross-validation. Similarly, Kulkarni et al. [96] used a recurrent neural network (RNN) to predict rice crop yields by looking at several activation functions to improve prediction accuracy and analyzing soil characteristics, nutrient measurements, and historical rainfall data spanning 31 years. These studies collectively demonstrate the advancements in ML and DL technologies in accurately predicting crop yields, which is critical for optimizing agricultural practices and enhancing food security globally.

- Biotic and abiotic stress detection

The control of biotic (diseases and pests) and abiotic (environmental) pressures in agriculture is greatly improved by the application of ML and L. This methodology begins with comprehensive data collection, utilizing high-resolution images from drones and satellites, along with sensor data from IoT devices in fields, to capture real-time environmental conditions and historical agronomic data. These datasets are processed and analyzed using advanced algorithms: CNNs for image analysis to detect issues like weed infestation or disease symptoms, and RNNs to handle time-series data from sensors for environmental pattern recognition. Integrated multimodal data are then employed to train more complex models, such as Multi-Layer Perceptron (MLP) or hybrid models, enabling predictive analytics. These analytics power decision support systems that forecast potential biotic and abiotic stresses and suggest optimal agricultural practices, including the precise timing and combination of fertilizers and pesticides, and efficient irrigation schedules. Learning models can classify a variety of biotic and abiotic stresses, using more than 25,000 photos. This methodology offers excellent dependability and adaptation to specific illumination levels, enabling accurate stress management in real-world scenarios. Wulandhari et al. [97] developed a deep convolutional neural network to manage crop health issues using crop images. A hybrid network that employed a transfer learning method known as the Inception-Resnet architecture was trained using the ImageNet dataset. Experiments were then carried out to adjust hyperparameters like learning rate and epoch count. During training and testing, the authors' accuracy rates were 96% and 86%, respectively. Using CNN and image segmentation, Watchareeruetai et al. [98] presented a novel approach for detecting and assessing plant nutritional deficits. A dataset consisting of 3000 leaf images was collected and used for experimentation. An environment with real-time nutrition management was used to validate the results. In Ghosal et al. [99], using destructive sampling, soybean leaves exhibiting signs of deficiencies such as potassium and iron were physically gathered in the field, resulting in a dataset of 25,000 labeled leaf images. Using a CNN classifier, the researchers achieved a high 94% accuracy in symptom identification. Their machine vision-based approach offers a swift and accurate method for detecting early stress symptoms in agriculture and is resilient to variations in illumination and suitable for large-scale applications. Robotic platforms have also been used to implement ML algorithms for plant disease identification. For example, an Unmanned Aerial Vehicle (UAV) was used to identify citrus greening, and the best model was identified by applying popular ML techniques such K-Nearest Neighbor, linear SVM, coarse gaussian SVM, standard gaussian SVM, and basic and advanced decision trees. This paper addresses research vacuum by comparing the performance of ML models with popular DL models for the classification of healthy and sick leaves, such as AlexNet, ResNet-50, VGG-16, etc. [100]. In a strawberry greenhouse, a mobile robot was utilized to identify illness using an SVM algorithm; the findings demonstrated a considerably lower prediction error [101]. Another study classified healthy and diseased vine leaves using one-class classifiers and local binary patterns [102]. Additionally, deep learning models automate and optimize harvesting processes, predict the best times for harvest, and facilitate post-harvest produce sorting based on maturity, thus enhancing market readiness and reducing losses. Real-time monitoring and the creation of field and feed maps allow for precise, variable interventions across different field zones, ensuring resources are utilized effectively. The methodology also incorporates cognitive solutions that analyze soil state, weather forecasts, and potential pest threats to provide actionable insights for crop management. This approach is continuously refined through feedback mechanisms and iterative improvements, with systems designed to adapt and learn from new data and farmer feedback to enhance prediction accuracy and model relevance. Sambasivam et al. [103] demonstrated the use of CNN models to detect diseases in cassava crops using a pre-processed dataset of 10,000 labeled images, achieving a high accuracy rate. Similarly, Ramcharan et al. [104] employed deep CNNs to identify diseases and pests in cassava using a dataset of 11,670 images, with significant efficiency validated by confusion matrix metrics. Mohanty et al. [105] detected crop diseases using deep CNNs trained on a large dataset of smartphone-captured images of diseased and healthy plant leaves, achieving high accuracy and F1 scores. Amara et al. [106] applied a CNN architecture based on LeNet to recognize disease in banana leaves, achieving notable F1 scores, while Dos Santos ferreira et al. [107] used a CNN for weed identification in soybean crops with high accuracy, using images captured by drones and processed via the SLIC algorithm. Through reliable data annotation and model selection, deep learning improves the accuracy and efficiency of mixed-seed detection and counting. The YOLOv5 model was trained using datasets of five different seed types that were annotated and enhanced using a Canon camera and the Robo-flow platform. The model achieved 96.96% recall, 94.81% precision, and 68.62% mAP [108]. This method simplifies the counting of seeds and has potential uses in precision farming and yield estimation in the future. A machine learning-based device using spectral data (notably at 680 and 760 nm) and a decision tree classifier accurately detected and estimated groundnut bud necrosis virus severity in tomatoes with over 93% accuracy. Integrating a spectral sensor and display, the device provided real-time severity assessments, enabling timely disease management and supporting crop health [109]. These studies highlight the effectiveness of ML and DL in enhancing disease detection, and environmental management in agriculture, significantly reducing the economic and environmental costs associated with traditional farming practices. This approach greatly increases productivity, environmental sustainability, and economic viability while simultaneously addressing the pressing demands of crop management and advancing sustainable agriculture practices through precision farming techniques.

- Intelligent harvesting techniques

By integrating cutting-edge technologies like smart sensors, robotics, UAVs, IoT devices, and computer vision techniques based on ML and DL models, intelligent harvesting techniques are transforming agriculture by lowering human labor [110]. Compared to conventional techniques, these intelligent systems offer numerous benefits, such as lower labor costs, improved crop yield accuracy, and more economical production. These systems not only optimize the harvesting process, but also improve the quality and timing of harvests, ensuring crops are picked at their peak [111–113]. Labor shortages in agriculture, particularly noted in Japan, have accelerated the adoption of robotic harvesting systems. For example, Sakai et al. [114] developed a machine vision-based robot for asparagus harvesting that operates three times faster than human labor, using laser sensors to accurately measure 3D distances for effective harvesting. Similar advancements have been made for other crops; Monta and Namba [115,116] explored laser sensors and color cameras for tomato and strawberry harvesting, respectively, achieving significant efficiencies in crop handling and processing. Zhang et al. [117] utilized Region-CNN for object detection in apple orchards, aiding in precise harvest timing decisions. The application of spectral and thermal imaging also supports the detection and management of fruit and vegetable harvests ([118,119]). Advanced ML techniques have been specifically tailored for various harvesting challenges. Applied principal component analysis can be used to distinguish between mechanically harvested and unharvested apples, enhancing the mechanical harvesting process. Similarly, Pise and Upadhye [120] implemented Naive Bayes and SVM algorithms for grading harvested mangoes, enhancing profitability by ensuring quality and maturity classification. The effectiveness of these intelligent systems is further exemplified in the specialized harvesting robots tested and developed for real-field conditions. Robots developed for tomato harvesting have utilized X-means clustering, a derivation of the

K-means method, to improve maturity recognition [121]. An SVM with a radial basis function (RBF) was successfully applied for apple recognition, demonstrating the feasibility of these systems in actual farm settings [122]. Moreover, ongoing research continues to explore and refine ML models for agricultural applications. Studies have compared various ML algorithms to optimize fruit recognition and classification processes. For instance, the use of a tractor system equipped with an SVM and Viewpoint Feature Histogram (VFH) effectively localized and detected broccoli, showcasing significant improvements when temporal filtering was incorporated [123]. These intelligent harvesting techniques enable precise crop monitoring, optimal harvesting timing, and efficient post-harvest processing, fundamentally transforming the agricultural landscape towards greater sustainability and productivity.

2.3.3. Internet of Things (IoT) in Precision Agriculture

The major goals of different IoT-based agricultural applications in specialized fields include tracking, monitoring, and control. These applications fall into the following major categories: Water Monitoring and Control (7%), Disease Monitoring (5%), Air Monitoring (5%), Fertilization Monitoring (4%), Precision Farming (16%), Soil Monitoring (13%), Temperature Monitoring (12%), Humidity Monitoring (11%), Animal Monitoring and Tracking (11%), and Irrigation Monitoring and Control (16%) [124] (Figure 4). Multiple agricultural operations are improved when connected technologies, such as sensors and UAVs, are integrated into agriculture. Agricultural ecosystems may now be continuously monitored and managed thanks to this technology, which lessens the need for direct human intervention outside of crises. To maintain ideal criteria, including soil characteristics, crop health, and environmental conditions, precision agriculture makes use of these interconnected systems. Data from sensors positioned across fields is transferred to a cloud for processing, enabling remote monitoring and control. By ensuring accuracy in the application of herbicides, fertilizers, and water, this technique helps avoid problems like animal encroachment in fields. Both digital and analogue sensors are essential for efficient operation; digital sensors analyze data more quickly and accurately by interacting directly with cloud systems. Common sensors in agriculture include soil moisture sensors, electrochemical sensors, and optical sensors, each contributing to a comprehensive understanding of field conditions.

A central location coordinates data from geographically dispersed sensors that monitor environmental variables as part of wireless sensor networks (WSNs). These data are then processed and analyzed in the cloud, employing intelligent algorithms to enhance decision-making in real time. The integration of artificial intelligence with WSN allows for sophisticated monitoring and intelligent decision-making. Huge data collection from IoT systems is essential for developing big data analytics in agriculture. These data contribute to making informed choices that boost yield and prevent waste. The data collected are analyzed to determine the optimal amounts of agricultural inputs required, thus enhancing the efficiency and sustainability of farming operations. These systems use algorithms like RNN and LSTM to ensure the efficient operation of sensors, extending their runtime significantly. Recent advancements include AI-driven sensor networks that classify land suitability post-harvest and improve the performance and energy consumption of sensor nodes. Better management of the sensor network is the outcome of intelligent processing of the data produced by nodes. After each cultivation, the authors of [125] classified land as appropriate, more suitable, somewhat suitable, or unsuitable using an AI-driven sensor network. In [126], the authors created a ZigBee module and Arduino microcontroller to create a power-efficient WSN that could monitor and regulate key factors that affect crop development, including soil and weather, in Florida, USA. The authors of [127] combine sensor nodes with AI systems to optimize each node's performance and data transmission, thereby lowering the nodes' power consumption. Using a Li-ion battery, an RNN-based Long-Short-Term (LSTM) network was developed that ensures 180 days of autonomous operation, extending the life of a single sensor. The suggested approach keeps an ongoing eye on the dynamics of plant leaf growth. Shadrin et al. [128] describe an autonomous system that uses an Internet of Things-based cloud platform and low-power sensor nodes to estimate the amount of phosphorus in soil using artificial neural networks. A dynamic power management system is incorporated by the authors to ensure a balance between energy usage and estimation accuracy. The authors provide a GA-optimized WSN for applications in precision agriculture in [129]. Furthermore, intelligent systems like those described by [130], which employ IoT and smart image recognition to detect crop maturity, are instrumental in enhancing decision-making processes in agriculture.

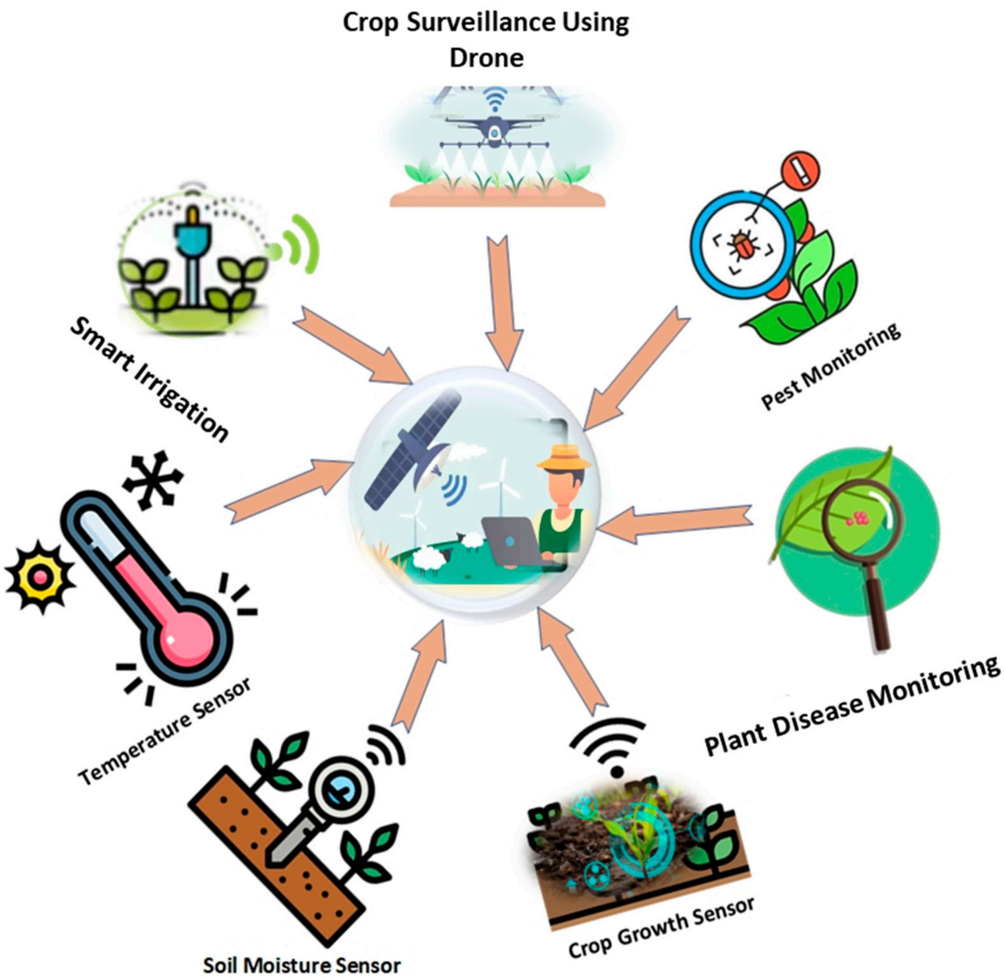


Figure 4. IoT-based monitoring systems in precision farming.

Therefore, we conclude that combining artificial intelligence with WSN and IoT is essential to ensuring the highest possible crop output. IoT plays a pivotal role in modern agriculture, offering solutions that range from basic monitoring to advanced predictive analytics. By leveraging IoT, precision agriculture can achieve higher productivity and sustainability, aligning with the goals of agriculture 4.0. Despite the benefits, the deployment of IoT in agriculture faces challenges such as data privacy, network security, and the integration of various IoT devices and platforms. Future research should be directed toward overcoming these challenges, enhancing the interoperability of IoT systems, and developing more robust models for real-time predictive analytics in agriculture.

2.3.4. Variable-Rate Technology (VRT) in Smart Farming

In theory, precision farming addresses differences in soil type, organic matter, nutrient needs, yield, and pests across a field. Variable treatments are commonly applied using map-based and sensor-based approaches. A map-based variable-rate application system uses a pre-made map, also known as a prescription map, to modify the application rate. The input concentration is adjusted as the applicator passes across the field, using the field position from a GPS receiver and a prescription map of the intended rate. Real-time data are utilized in the sensor-based technique to regulate the dosage and location of a particular therapy [131].

- Map-Based Technologies for Variable-Rate Application

Using the field position from a GPS receiver and a prescription map of the desired rate, the map-based variable e-rate application system modifies the application rate based on a preset computer map, also referred to as a prescription map; the amount of input varies as the applicator moves through the field. A single element or a mix of factors, including soil type, color, texture, topography, crop yield, and field scouting data, are used to determine the required application rate and the remotely sensed indices. In any case, users keep control over the application rate. The advantage of this method is that the quantities are predetermined and, therefore, there would be no fear of running out or mixing excess products, as demonstrated in Figure 5. However, one of the drawbacks is that if the weather changes or the temperature varies, there would be variation in soil characteristics, leading to the misplacing of inputs, which implies the need for the digital map to be dynamic [132]. Map-based control systems have been developed into commercially available products, such as 20/20 SeedSense (Manufacturer: Precision Planting LLC) is located in Wamego, Kansas and Rate Controller 2000 [133], as shown in Figure 6.

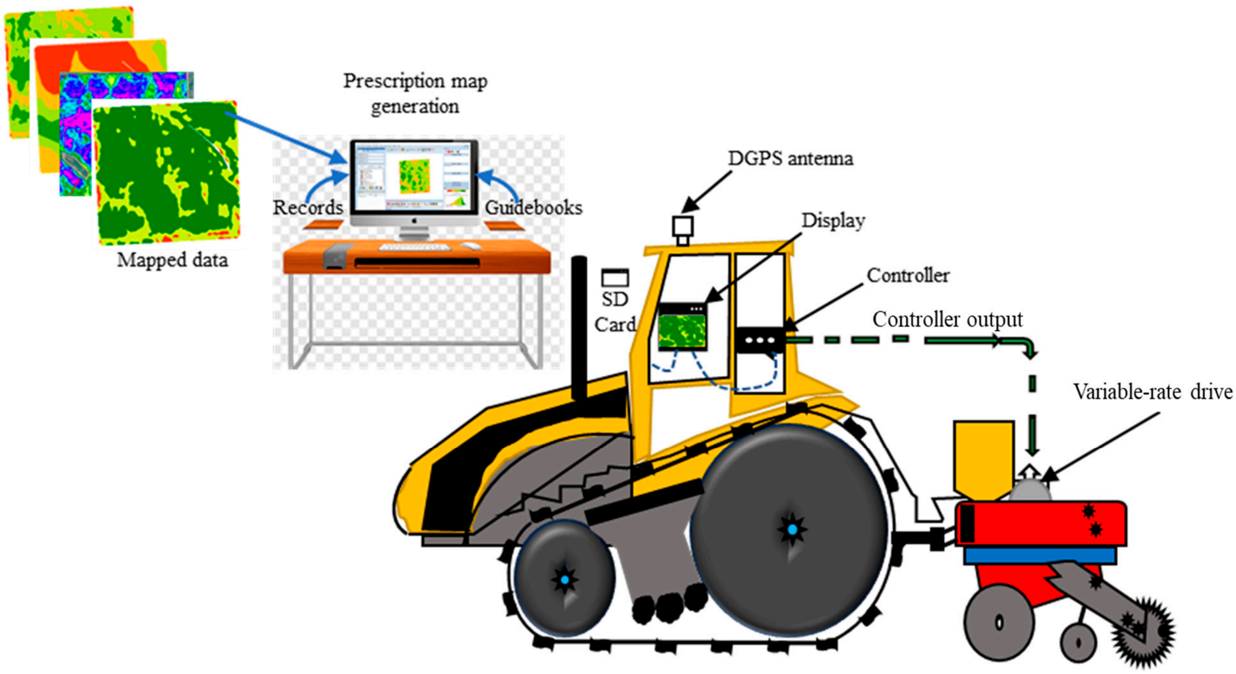
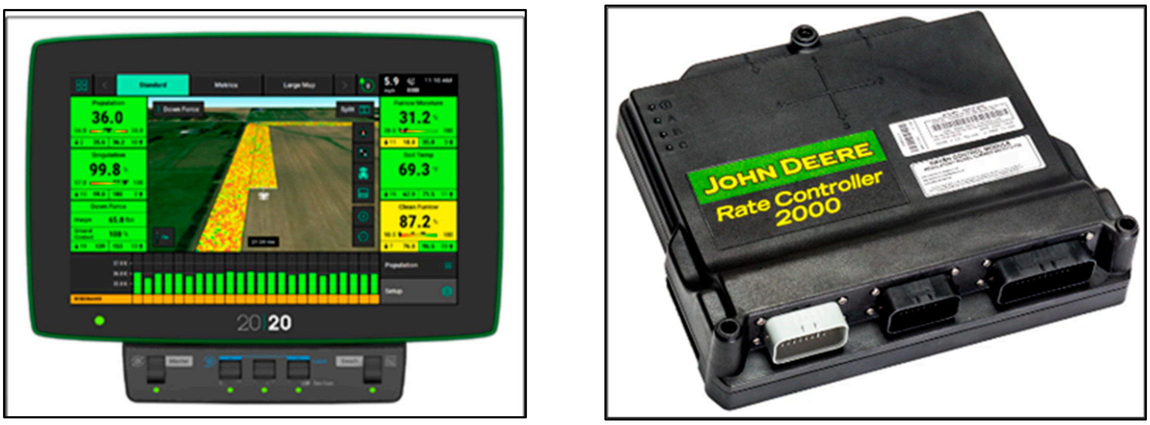


Figure 5. Map-based variable-rate application.



(**a**) (**b**)

Figure 6. Map-based variable-rate controller: (**a**) 20/20 SeedSense (Precision Planting); (**b**) Rate Controller 2000. Sensor-based technologies for variable-rate applications.

Sensor-based VRAs (Figure 7) operate without the need for a map or a positioning system. The applicator's sensors measure crops or soil variables while in motion. The precise input requirements of the soil or plants are determined by a control system using this continuous flow of data. After that, the data are passed from the control system to a sub-controller, which sends the input to the precise spot detected by the sensor [134,135]. Sensor measurements, such as plant reflectance indices, can be used to reduce the complexity of data; the popular normalized difference vegetative index (NDVI) is one example that is based on crop reflectance in the red and near-infrared (NIR) bands. Commercially accessible devices made using sensor-based systems include the John Deere smart sprayer, which uses mobile video sensors to identify weeds or nutrient stress and administer varying rates of application, as shown in Figure 8. This method does not necessarily require a positioning system or extensive pre-application data analysis. However, recording and geo-referencing sensor data enables future site-specific crop management, creating prescription maps for subsequent operations and providing an "as applied" record for growers.

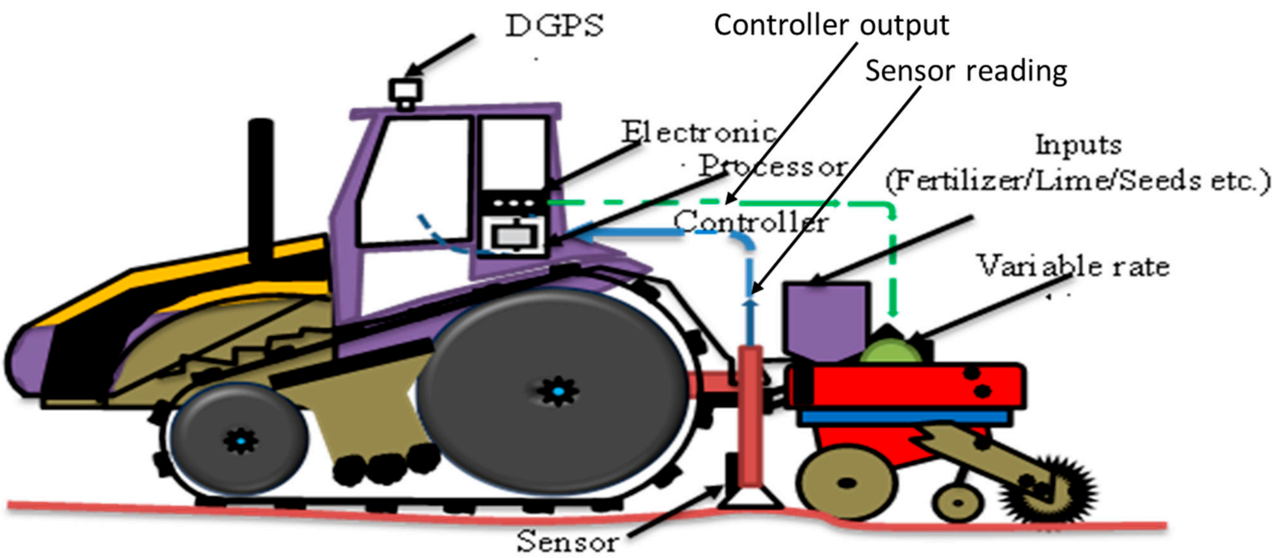


Figure 7. Sensor-based VRT.

(a) (b)

Figure 8. Sensor-based variable-rate technology for site-specific input management: (**a**) adaptive control system applying precise fertilizer rates; (**b**) real-time crop monitoring.

Variable-rate technology (VRT) in agriculture employs real-time data from sensor-based systems to tailor fertilizer applications precisely to the needs of specific crop locations. This technique is critical in managing nutrient application dynamically, optimizing the usage based on real-time observations of soil and plant conditions. Sensors like Crop Circle and Green Seeker play a pivotal role, measuring plant canopy reflectance in various spectral bands to compute vegetation indices such as the normalized difference vegetation index (NDVI). The NDVI, the most commonly used index, is calculated by comparing the reflectance in the near-infrared and red bands; this helps to determine plant health and thus the required fertilizer dosage [136,137].

These sensor-based systems ensure that nutrients are applied efficiently, avoiding both under- and over-fertilization, Figure 8. The system's ability to adjust application rates in real time prevents wastage and environmental damage while improving crop yield and quality. For example, nitrogen management adjusts urea application based on the greenness of crop leaves, targeting specific zones within a field that display varying nutrient needs [138]. Accurate nitrogen measurement is facilitated by tools such as the SPAD meter, which directly assesses nitrogen concentration in the canopy, guiding fertilizer application to optimize plant growth [139,140]. Moreover, the precise application is dependent on the system's response time, which must be minimized to avoid delays that could affect the applicator's accuracy and, consequently, crop yield [141]. Variable-rate applications are also dependent on sophisticated management strategies. The Oklahoma (OK) and Missouri (MO) methods illustrate two different approaches to nitrogen application based on NDVI data. The OK method integrates more complex data, including yield potential and growth conditions, directly into an on-board computer system, facilitating precise nutrient application with minimal user intervention [142]. These advanced VRT systems, which combine sensor data with real-time processing and feedback loops, are essential for modern precision agriculture. They allow farmers to apply the correct amount of nutrients at the right time and place, enhancing crop management efficiency, reducing environmental impact, and increasing farm profitability. Despite its advantages, the adoption of VRT is hindered by high initial costs and the complexity of its operational technologies, which can be daunting for farmers [143,144]. Furthermore, this technology's reliance on sophisticated hardware and data management systems necessitates a large initial outlay of funds, as well as training, which further hinders its general adoption. Future VRT research will concentrate on combining it with cutting-edge developments like machine learning and connected gadgets. It is projected that this integration will increase the accuracy and effectiveness of VRT applications, which could reduce expenses and make them more accessible to a larger group of farmers [145,146]. These developments could improve crop management and resource utilization by streamlining decision-making in VRT through improved automation and data analysis. In 2024, an estimated 47.2 million acres in the United States was planted with winter wheat, 91.5 million acres with corn, and 86.4 million acres with soybean [USDA, NASS, Survey 2024]. However, the adoption of variable-rate technology (VRT) for these crops remains limited. In 2016, VRT was adopted on 37.4% (33.6 million acres) of corn-planted acres, followed by 18.8% (6.39 million acres) for winter wheat in 2017, and 25.3% (8.5 million acres) for soybean in 2018, as shown in Figure 9. Despite its potential to reduce costs, VRT adoption is still not widespread across U.S. farms [147,148]. Adoption rates tend to be higher among large farms, with lower uptake among smaller farms, indicating potential benefits of scale [149]. Using linear regression to estimate VRT adoption for 2024, the projected adoption rates are 44% for corn, 26% for soybean, and 22% for wheat.

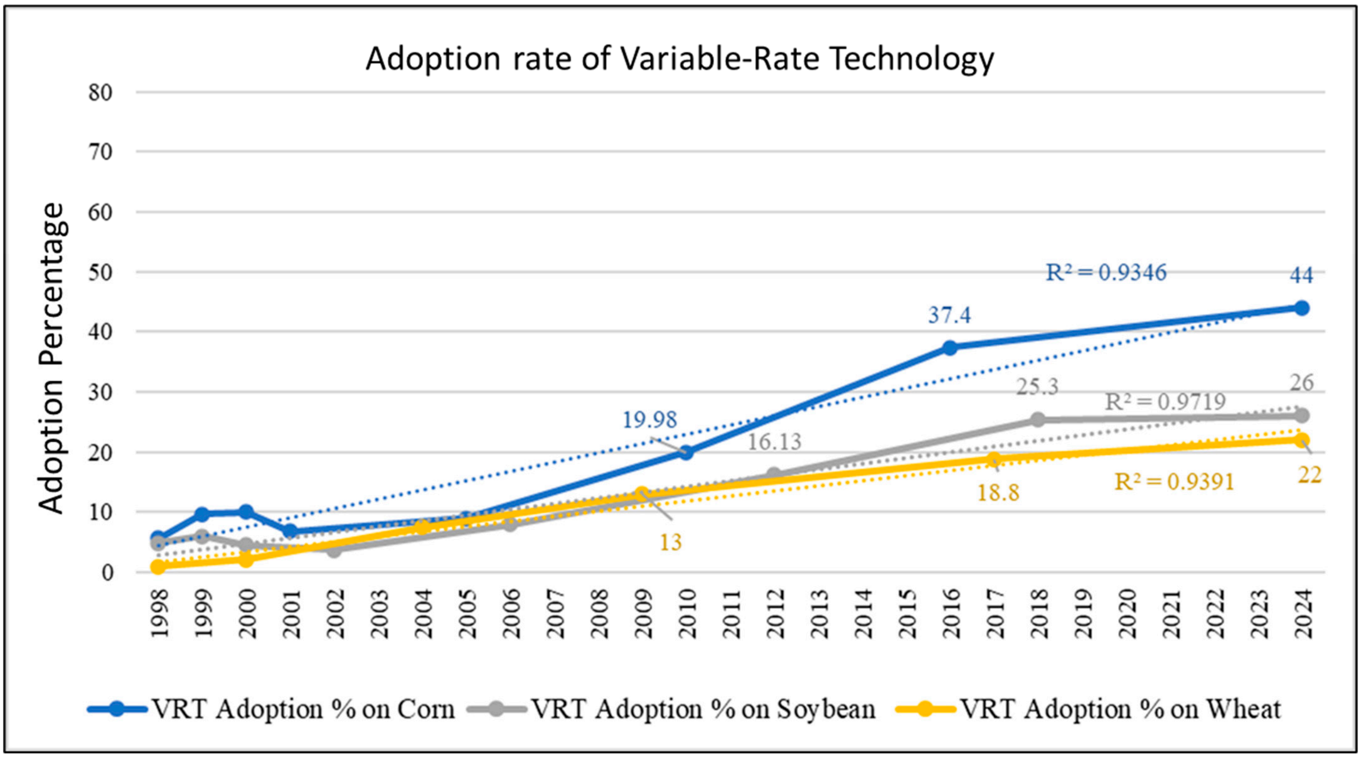


Figure 9. The adoption rate of variable-rate technology for corn, soybean, and wheat.

Corn is high in nitrogen and in demand [150]; it stands to gain substantially from the targeted delivery of nitrogen fertilizers. This precision approach enhances corn growth more effectively than in other crops like beans [151] or wheat. Consequently, corn growers are likely to experience more pronounced benefits, including improved yields and resource efficiency, from adopting variable-rate technology.

3. Conclusions

Modern technologies like AI, ML, DL, and the Internet of Things have revolutionized farming methods through precision agriculture. This integration of cutting-edge technologies aims to optimize outputs with precise inputs, revolutionizing the agriculture industry. Through real-time data collection and analysis, these technologies enable farmers to make informed decisions and enhance productivity while minimizing environmental impacts. Traditional farming methods are increasingly challenged by environmental and economic pressures, necessitating a shift towards more sustainable practices. Precision agriculture offers a solution by leveraging advanced technologies to create a more controlled and resource-efficient farming environment. By conservatively utilizing resources such as water, fertilizers, and pesticides, precision agriculture reduces costs and environmental footprints, contributing to long-term sustainability. Smart farm management benefits significantly from advanced predictive models and automated systems. Techniques such as regression models and convolutional neural networks (CNNs) enable accurate forecasts of weather patterns, soil properties, and crop health. This predictive capability allows farmers to optimize farming operations, from soil management to crop monitoring, in real time. Additionally, IoT-enabled sensors and actuators provide continuous data collection, further supporting data-driven decision-making in agriculture. Furthermore, advancements in remote sensing through satellite data from programs such as Landsat and Sentinel significantly enhance environmental monitoring capabilities. These satellites provide high-resolution, real-time data crucial for precise crop management, land cover classification, and vegetation analysis, further strengthening the precision agriculture ecosystem. Looking ahead, agriculture's future is ripe with opportunities for innovation. NLP-driven chatbots could offer personalized advice, improving farmers' access to expert knowledge. Moreover, advancements in predictive algorithms and hybrid technologies promise further improvements in resource management and sustainability. As the global population approaches 9.7 billion by 2050, the agricultural sector faces growing challenges. The combination of these cutting-edge technologies offers encouraging answers and opens the door to more sustainable and productive farming methods. To achieve fair access and adoption, governments, technology companies, and the farming community must work together to realize these benefits. The alignment of these technical developments with the 2030 Agenda's Sustainable Development Goals (SDGs) is another important point to emphasize. SDG 2 (Zero Hunger) is directly supported by precision agriculture's use of cutting-edge technologies like artificial intelligence (AI), the Internet of Things (IoT), and machine learning (ML), which increase productivity and improve food security. By optimizing resource use, lowering environmental footprints, and improving land management, these technologies also support sustainable practices that align with SDGs 12 (Responsible Consumption and Production), 13 (Climate Action), and 15 (Life on Land). These developments have the potential to make agriculture a more resilient and egalitarian sector by connecting technological improvements with global sustainability goals.

4. Future Perspectives

The future of agriculture lies at the intersection of technology and sustainability, with AI models playing pivotal roles in shaping the industry. As we look ahead, several key trends and opportunities emerge for the continued advancement of sustainable agriculture:

- Advanced Algorithms: The further exploration of ML, DL, and hybrid algorithms holds promise for improving resource management and sustainability in agriculture. By developing more sophisticated models, we can enhance predictive capabilities and optimize farming operations for maximum efficiency.
- Data Integration and Analysis: The integration of diverse data sources, including satellite imagery, sensor data, and weather forecasts, presents opportunities for comprehensive analysis and informed decision-making in agriculture. Advanced data mining and management tools will be essential for extracting valuable insights from large datasets.
- Smart Farming Technologies: Efficiency and advances in agriculture will be fueled by ongoing innovation in smart farming technology, such as robotics, drones, and sensors enabled by the Internet of Things. More sustainable farming methods are made possible by these technologies, which allow for the real-time monitoring and management of crops, livestock, and environmental conditions. In what ways might

3D mapping and monitoring support each farm's sustainability objectives? How might unmanned hybrid (aerial–ground) drones enhance agricultural monitoring operation management [152]?

- AI Applications in Irrigation Science and Water Use Efficiency: Artificial intelligence is transforming irrigation science and water usage efficiency, solving water shortage concerns exacerbated by climate change. Precision agriculture, which incorporates AI-powered technologies such as smart sensors, IoT, and wireless sensor networks, optimizes irrigation by considering soil moisture fluctuation and crop water requirements [153]. Smart irrigation delivers accurate water delivery, reducing waste and crop stress while enhancing resource management [154]. Conventional irrigation techniques frequently lead to unequal water distribution, which causes inefficiencies such as nutrient leaching, runoff, and yield decreases, since they fail to take into consideration dynamic soil and weather conditions. Wireless sensor networks, IoT-enabled smart sensors, and AI-driven models have all been used in recent developments to improve irrigation scheduling and track environmental factors in real time [155–157]. AI-powered irrigation control systems provide optimal water usage by dynamically adjusting water applications based on crop responses, predictive analytics, and external environmental disturbances. Although there has been a lot of progress, future studies ought to focus on strengthening AI integration with current smart irrigation technologies, enhancing data-driven decision support systems, and tackling issues with system scalability, energy efficiency, and data accuracy. In the face of climate uncertainty, expanding AI applications in irrigation research will be essential to attaining the sustainable management of water resources and ensuring global food security.
- Digital Agriculture Platforms: The emergence of digital agriculture ecosystems and platforms will make it easier for participants in the agricultural value chain to work together and exchange knowledge. These platforms can provide farmers with access to market information, financial services, and agronomic advice, empowering them to make informed decisions and improve productivity.
- Policy Support and Investment: Governments and policymakers play a crucial role in supporting the adoption of cutting-edge technologies in agriculture. Policies that promote investment in technology infrastructure, training programs for farmers, and research and development initiatives will be essential for driving innovation and ensuring equitable access to agricultural technologies.
- Addressing Barriers to Adoption: Overcoming challenges such as high costs, training requirements, and data security concerns will be critical for the broader adoption of AI, ML, DL, and IoT in agriculture. Collaborative efforts between governments, technology providers, and the farming community are needed to address these barriers and realize the full potential of technology-driven agriculture.

The future of sustainable agriculture is bright because of advancements in cutting-edge technologies like AI, ML, DL, and IoT. We can create a more resilient, efficient, and environmentally sustainable agriculture system to feed the growing global population while protecting natural resources for coming generations by utilizing the potential of these technologies and embracing innovation.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	**Full Form**
AI	Artificial Intelligence
IoT	Internet of Things
PA	Precision Agriculture
GPS	Global Positioning System
GIS	Geographic Information Systems
NDVI	Normalized Difference Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
VSSI	Vegetation Soil Salinity Index
EVI	Enhanced Vegetation Index
NLVI	Non-Linear Vegetation Index
DVI	Differential Vegetation Index
GRVI	Green Ratio Vegetation Index
SI	Salinity Index
ERSI	Enhanced Residues Soil Salinity Index
CRSI	Canopy Response Salinity Index
CI	Clay Index
GI	Gypsum Index
BI	Brightness Index
NMDI	Normalized Multi-Band Drought Index
$L(\lambda)$	Radiance
$\rho(\lambda)$	Reflectance
USGS	United States Geological Survey
NASA	National Aeronautics and Space Administration
ESA	European Space Agency
SWIR	Shortwave Infrared
NIR	Near-Infrared
R	Red
B	Blue
G	Green
π	Pi (Mathematical Constant)
θ	Solar Zenith Angle
NRBS	Nitrogen-Rich Biosensor Spots
DL	Deep Learning
ML	Machine Learning
VRT	Variable-Rate Technology
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
DT	Decision Tree
RF	Random Forest
ANN	Artificial Neural Network
MSE	Mean Squared Error
LSTM	Long Short-Term Memory
TP	True Positives

TN	True Negatives
FP	False Positives
FN	False Negatives
T	Number of trees in Random Forest
P(y|X)	Posterior probability of data point y given X
Sentinel-2	A satellite mission for Earth observation by the European Space Agency
Landsat-8	A satellite for remote sensing managed by NASA and USGS
AS7341	A spectral sensor commonly used in agricultural remote sensing
PCM	Predictive Crop Modeling
HRI	High-Resolution Imagery
EL	Ensemble Learning
RS	Remote Sensing
ELM	Extreme Learning Machine
SOC	Soil Organic Carbon
pXRF	Portable X-ray Fluorescence
DNN	Deep Neural Network
UAV	Unmanned Aerial Vehicle
RNN	Recurrent Neural Network
MODIS	Moderate-Resolution Imaging Spectroradiometer
SNAP	Sentinel Application Platform
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
LASSO	Least Absolute Shrinkage and Selection Operator
GA	Genetic Algorithm
RGB	Red, Green, Blue (color model used for images)
SIF	Solar-Induced Chlorophyll Fluorescence
pH	Potential of Hydrogen
MLP	Multi-Layer Perceptron
YOLO	You Only Look Once (a family of real-time object detection models)
RBF	Radial Basis Function (a kernel function used in SVM)
PCA	Principal Component Analysis
VFH	Viewpoint Feature Histogram (used in object recognition and classification)
mAP	Mean Average Precision (used to evaluate object detection models)
F1 Score	A measure of a model's accuracy, combining precision and recall
Inception-ResNet	A hybrid deep learning architecture combining Inception and ResNet models
SLIC	Simple Linear Iterative Clustering (an algorithm for image segmentation)
DL Models	Deep Learning Models
WSN	Wireless Sensor Networks
Li-ion	Lithium Ion
SPAD	Soil Plant Analysis Development
VRA	Variable Rate Application
NLP	Natural Language Processing
AI-ML	Artificial Intelligence and Machine Learning
USDA	United States Department of Agriculture
NASS	National Agricultural Statistics Service

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