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Review

Precision Agriculture Through a Real-Time Systems Perspective: A Narrative Review

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Abstract

Precision agriculture employs state-of-the-art technologies to improve the economic viability, sustainability, and efficiency of agricultural practices. This paper offers a thorough review of precision agriculture, with an emphasis on real-time systems as a foundation for understanding the integration and impact of major technologies. We examine technologies such as digital twins, mobile applications, autonomous systems, location-aware technologies, edge computing, and Wireless Sensor Networks (WSN) that are revolutionizing agricultural processes. We also discuss the potential of other sensing techniques to enhance precision farming, including image analysis, sensory and chemical analysis, and physical state detection. Additionally, the roles that data transmission protocols, artificial intelligence (AI), and machine learning play in maximizing real-time data processing and decision-making are examined. We emphasize the main challenges and limitations in precision agriculture, such as data interoperability, scalability, and system integration. With a focus on market trends and local issues, we examine how AI, real-time systems, sensor technologies, and financial constraints impact the growth of precision agriculture. These advancements have an impact on precise monitoring, post-harvest management, and human health. Lastly, we provide suggestions for successful integration and future developments in precision agriculture, emphasizing design, engineering, and creative approaches to assist the field's ongoing development.

Keywords: digital agriculture; precision agriculture; real time systems; smart farming

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1. Introduction

Agriculture provides food and other necessities for human civilization. However, industrial farming has raised emissions of greenhouse gases, contaminated water, and deteriorated soil [1,2]. In addition, it has resulted in food that has been associated with food-borne diseases, obesity, and malnutrition. The current goal of emerging technology is to reverse these effects. Smarter, more sustainable farming is made possible by computing systems' ability to identify, analyze, and react to dynamic behaviors [3]. Precision agriculture is increasingly being used to increase agricultural productivity, lower costs, and promote environmental resilience [4]. Weather forecasting, plant and soil monitoring, irrigation and fertilizer management, insect detection, harvest optimization, automation,

supply chain analytics, and sustainable energy usage are some of the uses of precision agriculture. By detecting nutritional deficiencies, forecasting illnesses, and maximizing harvests, these technologies improve output and sustainability. However, difficulties still exist. Plant variability, efficient data processing, and ethical issues such as data privacy and potential plant damage must all be addressed by systems [5].

1.1. Precision Agriculture

Climate change and environmental degradation are two major effects of unsustainable agriculture practices. It accounts for 20–25% of global greenhouse gas emissions, while deforestation and water resource extraction further endanger biodiversity and ecosystem health [6]. Sustainable methods that combine production with environmental and human health are increasingly necessary to meet the world's food demands. By providing farmers with cutting-edge tools to make data-driven selections for crops, animals, and land management, precision agriculture provides a workable solution [7,8]. Industrial farming, on the other hand, is time-consuming, is highly dependent on physical labor, and frequently damages soil quality, lowering yields and nutritional value [9]. The overuse of pesticides and fertilizers contaminates the water and soil and poses major health problems [10]. Precision agriculture makes it possible to monitor crop and soil conditions in real time to increase yields, decrease waste, and improve sustainability by combining sensors, Unmanned Aerial Vehicles (UAVs), motion detection, real-time tracking, and Global Positioning Systems (GPS) [4,11]. But despite its potential, high technology prices and poor farmer knowledge remain barriers to precision agricultural implementation.

Precision farming practices strengthen the sustainability of food systems that directly affect human health by lowering exposure to dangerous chemicals and infections [12–16]. Water pollution, chemical residues in food and packaging, and unhealthy diets are examples of this crucial relationship. Food waste also represents the loss of resources, including soil, water, and energy, used in production. Furthermore, by building up neurotoxic compounds in the body, eating food tainted with chemicals and pollution can raise the chance of Parkinson's disease [17]. Long-term exposure, especially to compounds that damage dopamine-producing neurons, may raise the chance of Parkinson's disease [18]. Toxins that can disrupt nervous system function include heavy metals and herbicides. Chemicals that replicate the metabolic mechanisms that cause dopamine neuron degeneration, a characteristic of Parkinson's disease, such as paraquat [19] and rotenone, have been connected to neuronal damage. Neural deterioration may be accelerated by diets high in processed foods or deficient in antioxidants, which can worsen oxidative stress. Therefore, food-borne toxins and agricultural chemicals play a significant role in the development and progression of Parkinson's disease, with pesticides exhibiting the strongest environmental correlation [20]. Because food quality has such significant effects on human health and well-being, precision agriculture must prioritize it.

Using precision agricultural methods helps reduce the risk of exposure to harmful chemicals and pathogens [12–14]. Furthermore, the sustainability of the food system has a direct impact on human health [15,16]. Water pollution, exposure to chemical residues in food and packaging, and unhealthy diets are only a few instances of this significant relationship. All resources utilized to create food, such as energy, water, and soil, are included in the category of food waste. Food intake, especially the absorption of certain chemicals and pollutants, might contribute to the development of Parkinson's disease by accumulating neurotoxic substances in the body [17]. Heavy metals, insecticides, and other hazardous chemicals commonly found in food can accumulate over time and potentially interfere with the nervous system. Long-term exposure to various drugs, particularly those that impact the brain's dopamine-producing neurons, may raise the risk of Parkinson's

disease, according to studies [18]. In particular, chemicals such as paraquat [19] and rotenone [21], which are used in agriculture, have been linked to neuronal damage and are known to mimic the biochemical processes that lead to the degeneration of dopamine-producing neurons, a hallmark of Parkinson's disease.

Precision agriculture allows early identification of pests and crop diseases. It enables farmers to take preventive measures and control the spreading of diseases to other crops. This approach reduces the health risks associated with exposure by minimizing the use of hazardous chemicals and pesticides [14,22]. Farmers can improve health outcomes, especially for those with nutritional deficiencies, by monitoring crop nutrition and optimizing growing conditions to produce more nutrient-rich food [10,23–26]. Precision approaches reduce the adverse environmental consequences of agriculture by reducing greenhouse gas emissions, conserving resources, and promoting sustainability. Farmers can attain high yields with little to no chemical input by using precision irrigation [27], precision fertilization [7,28], and precision pest management [7,8,29]. This improves soil health, crop quality, and food safety [14,22,30]. By using sensor-based algorithms to determine appropriate application levels, early plant disease diagnosis and precision pesticide systems [8] further minimize pesticide consumption while increasing sustainability and production. Farmers can improve their management tactics and better understand crop-environment interactions by analyzing sensor data. Furthermore, animal welfare [31], a crucial component of livestock production and health, is supported by precision agriculture. Farmers can receive targeted treatment and lessen their dependency on antibiotics and other medications by using technologies that monitor livestock status and notify them of discomfort or disease [32].

Precision agriculture technologies have a significant impact on agricultural advancements when they are successfully integrated into the core of agriculture. They eventually improve the nutritional value of food consumed by humans, reduce the risk of exposure to hazardous chemicals and pathogens, and promote sustainable farming practices that improve both human health and the environment [25]. This research aims to investigate the application of precision agricultural technology in agriculture. It also clarifies the obstacles and constraints that must be overcome for this program to be implemented successfully. From this perspective, the authors aim to guide future advancements in the field and contribute to the growing body of knowledge on the application of technology in agriculture. The goal of this study is to thoroughly examine the key precision agriculture technologies and their impact on farming methods. It focuses on models that form the basis of precision agricultural analysis, including image analysis, sensory analysis, chemical analysis, and machine learning. The study also examines the role of precision agriculture in horticulture, emphasizing its direct impact on human health. The primary contribution of this study to the field is its unique perspective, which evaluates precision agriculture via the prism of real-time systems. By addressing limitations, highlighting possible study topics, and offering insights into design and integration from an engineering perspective, this work seeks to be a useful resource for researchers in the field.

1.2. Research Contributions

The main contributions of this paper are as follows:

- Comprehensive Survey—This paper provides an extensive review of more than 100 research articles covering key technologies in precision agriculture, including real-time systems, sensing methods, and AI applications.
- Unique Perspective—The paper evaluates precision agriculture through the lens of real-time systems, emphasizing their role in improving agricultural efficiency and decision-making.

- Sensing and Analysis Insights—It explores various sensing techniques such as image analysis, sensory, and chemical analysis and their applications in precision farming.
- AI and Data Communication—The study highlights the contributions of AI and data communication protocols in optimizing real-time data processing and decision-making.
- Design and Engineering Recommendations–The paper offers practical recommendations for the design and integration of precision agriculture technologies from both design and engineering perspectives.
- Identification of Limitations and Future Directions: It identifies key limitations in current approaches and outlines promising future directions for research and development in precision agriculture.

2. Method

2.1. Review Method

The main technologies and trends in precision agriculture are examined in this paper using a narrative review methodology. The strategy aims to provide a thorough grasp of the present status of the topic by synthesizing a wide range of studies and research findings. The narrative review approach was selected because of its adaptability in covering wide subjects and its capacity to give a summary of many viewpoints and ideas found across the literature [33,34]. This methodology allows for a qualitative study of various sources, which facilitates a deeper understanding of emerging trends and research gaps, in contrast to systematic reviews, which adhere to rigorous selection criteria. The following research questions are attempted to be addressed by the review:

- What are the key technologies advancing precision agriculture?
- How do sensing, analysis, and real-time monitoring improve agricultural practices?
- What is the role of AI and data communications (e.g., 5G/6G) in precision agriculture?
- What are the challenges, limitations, and future directions in the field?

2.2. Search Method

The review synthesizes both current and foundational research on precision agriculture. In particular, the review focuses on real-time systems, smart farming technologies, and environmental and health implications.

2.3. Keywords Searched

To find relevant material, we searched the Scopus, Web of Science, ScienceDirect, IEEE Xplore, SpringerLink, Wiley Online Library, MDPI, and PubMed databases. Credible institutional and industry sources were also used to supplement the search. Keywords searched included “precision agriculture”, “smart agriculture”, “digital farming”, “agriculture 4.0”, “artificial intelligence in agriculture”, “machine learning”, “IoT", ”UAVs", “wireless sensor networks”, “fertilizer management”, “pesticide application”, “soil quality monitoring”, “greenhouse gas emissions”, “climate change”, “environmental sustainability”, “food safety”, “occupational health”, and “neurodegenerative diseases”, adapted to database-specific indexing.

2.4. Coverage

The time frame includes papers from 2017 to 2026. Both crucial fundamental research and contemporary technology advancements were covered in these papers. Book chapters, conference proceedings, peer-reviewed articles, review papers, and a few technical reports were included in the collection if they directly addressed the main topic. Any non-English publications, editorials, and non-relevant studies were excluded.

3. Results

The study's findings on the major fields in which precision agriculture technologies are being used are presented in the sections that follow, together with a discussion of the possible advantages and difficulties of these applications.

3.1. Precision Agriculture–Technology

Smart farming raises agricultural output and quality by integrating sensor technologies and Internet of Things frameworks to build "intelligent farms". Precision irrigation, fertilization, and crop management are made possible by IoT, which makes it easier to collect and analyze data on crop yield, soil mapping, fertilizer use, and climate. For instance, IoT helps with crop management in peanut farming by gathering data for efficient decision-making. Sensing subsystems help make decisions in real time to enhance crop nutrition and soil health by detecting humidity and wind patterns. Research suggests that natural language mobile applications may be used by IoT-based agricultural monitoring systems to deliver fertilizer recommendations and irrigation schedules [35]. Similar technologies optimize groundnut farming practices [36]. Figure 1 illustrates the technologies that enable support for precision agriculture and smart farming practices, and Table 1 provides a summary of the technologies explored in the literature.

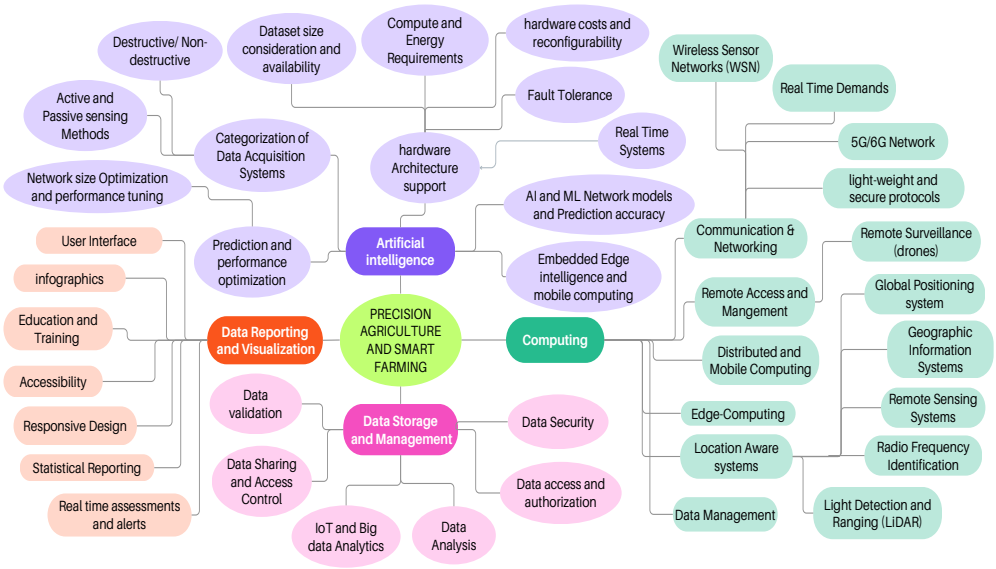


Figure 1. Technologies enabling precision agriculture and smart farming.

3.2. Real Time Systems in Precision Agriculture

Precision agriculture primarily relies on real-time systems (RTSs) since they allow for quick reactions to dynamic elements like crop health and soil moisture. These technologies optimize operations like pest management and irrigation, handle massive amounts of sensor data, and conduct real-time analysis as illustrated in Figure 2. RTS must also consider power and energy constraints, especially in distributed networks with widely scattered sensors and actuators. While maintaining agricultural responsiveness, efficient scheduling and real-time work management enable efficient resource utilization [37]. Time-sensitive processes are given priority by scheduling algorithms such as Earliest Deadline First (EDF) and Rate-Monotonic Scheduling (RMS) to ensure resource efficiency [38]. Figure 3 shows how scheduling separates jobs into three categories: firm, soft, and hard deadlines. Important tasks that must be completed within a specific time frame in order to prevent system failure include turning on irrigation systems and applying pesticides before environmental conditions deteriorate.



Figure 2. Real time systems driving various sub-domains in precision agriculture.

Soft deadline jobs, such as gathering non-urgent sensor data for long-term research or adjusting soil nutrient levels, may tolerate minor delays without negatively impacting overall performance. A *firm deadline task*, on the other hand, lies between hard and soft deadlines. Missing it might have a major effect on system performance, even if it is not as strict as a hard deadline. A work may not be processed or may be deleted if a strict deadline is missed; however, this does not result in a complete system failure.

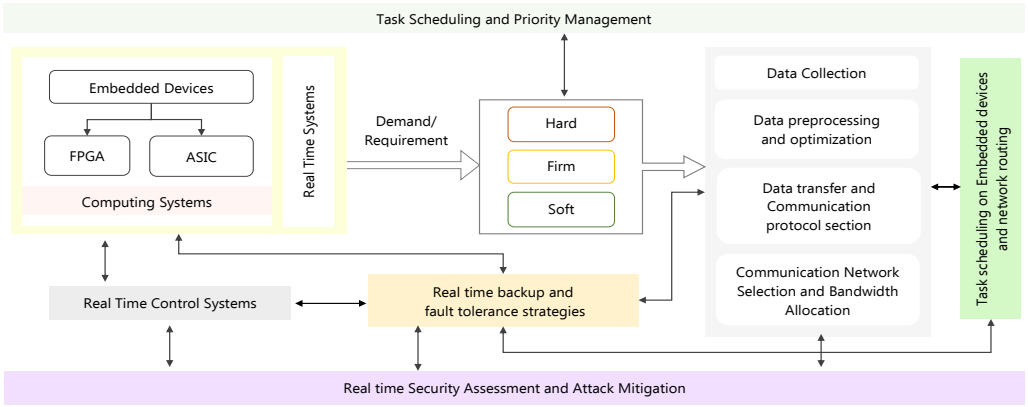


Figure 3. A typical real-time systems architecture for use in precision agriculture.

Table 1. Summary of technologies for precision agriculture: applications, range, and coverage.

Ref.	Tech.	Main Application	Range (R) and Power Consumption (P)	Coverage
[39]	GPS	Positioning and navigation of vehicles, machinery, and livestock; Precision agriculture	R: 20–200 km (satellite orbit) P: 1.5 W (receiver)	Global (continuous coverage)
[40]	GIS	Mapping, spatial data analysis, land use planning; Crop monitoring and field mapping	R: 1–100 km (dataset resolution) P: 3 W (PC/server processing)	Local, regional, and global

Table 1. *Cont.*

Ref.	Tech.	Main Application	Range (R) and Power Consumption (P)	Coverage
[41,42]	Remote Sensing	Environmental monitoring	R: 500 m–36,000 km (drone to geostationary satellite) P: 5–1000 W (platform/sensor dependent)	Local to global (depending on sensor platform)
[43]	UAVs	Aerial surveillance of crops, pest detection, field monitoring; Crop health and growth analysis	R: 5–50 km (UAV operational range) P: 100–500 W (small to large UAV + sensors)	Local (field-specific, customizable)
[44]	RFIDs	Livestock tracking, inventory management, supply chain management; Asset tracking	R: 0.1 km (100 m for active RFID) P: Passive: 0.05 W; Active: 0.5 W	Local (tracking within proximity)
[45]	Lidar	Mapping terrain, vegetation analysis, crop height measurement; Forest management, 3D field mapping	R: 0.2–0.5 km (UAV/ground LiDAR) P: 50–100 W (system dependent)	Local (typically ground-level scanning)
[46]	Terahertz	Monitoring plant health, detecting disease, water stress, and nutrient deficiencies	R: 5 m P: 1–5 W	Local (precise field-specific applications)
[5]	Power Management	Energy-efficient systems for sensors and devices in agricultural environments; Optimization of energy consumption in farms	R: <100 m (device-specific) P: 0.5 W	Local (specific to energy management systems)

3.3. Precision Agriculture Key Technologies

3.3.1. Wireless Sensor Networks (WSNs)

Wireless Sensor Networks (WSNs), which provide real-time monitoring of soil and ambient parameters, improve precision agriculture. Horizontal, vertical, and hybrid sensor topologies optimize network efficiency; horizontal and hybrid designs are more cost-effective and provide greater coverage than vertical ones. Precise nutrient management is made possible by integrated sensors like pH and NPK sensors, which increase crop yields and sustainability. LoRaWAN and Zigbee technologies are used by WSNs to send data to base stations for decision-making (Table 2). These technologies improve insect control, fertilizer management, and irrigation while lowering waste and environmental effect. WSNs increase agricultural productivity despite obstacles such as power consumption and network congestion (Table 3). Because disease outbreaks have the potential to wipe out crops, WSNs must set strict timelines (hard deadlines) to guarantee data communication, timely activation of control, and spraying events. Similarly, collecting pest information often provides an adjustable timeframe (soft deadlines) that may be adjusted as needed. Even while brief irrigation delays would not hurt crops, they are nonetheless permissible (firm deadlines) as long as work schedules adhere to strict deadlines and irrigation is finished on time.

Table 2. Wireless sensor network data transmission technologies [47]. Note: L (Low 1–100 mW), M (Moderate 100–500 mW), and H (High > 500 mW).

Transmission Modules and Range	Frequency and Data Rate	Node	Power Level	Communication Type
Zigbee (10–20 m)	2.4 GHz (20–250 Kbps)	65,000 nodes per network	L	Peer-to-peer
GPRS (in range of mobile network area)	900–1800 MHz (56–114 Kbps)	1000 nodes per network	H	Base station to device
LoRa (>10 km)	169 MHz, 868 MHz, and 433 MHz (0.3–50 Kbps)	10,000 nodes per gateway	M to H	Peer-to-peer
Bluetooth (1–100 m)	2.4–2.485 GHz (1–3 Mbps)	8 active nodes per piconet	L to M	Master–slave and peer-to-peer
WiFi (20–100 m)	2.4 GHz (2–54 Gbps)	32 nodes per network	H	Access point to device
Xstream (5–16 km)	2.4 GHz (10–20 Kbps)	7 channels, 65,000/channels	L	Peer-to-peer

Table 3. Real-time communication technologies in agricultural systems.

Range	Tech.	Protocols	Collision Avoidance	Security	RT Characteristics	Applications & Impact
Long	LPWAN (LoRaWAN, NB-IoT)	LoRaWAN, NB-IoT, ALOHA (for collision avoidance)	ALOHA, Retransmission (Random)	AES, TLS, IPSec	Low power, Low latency, Medium throughput	Remote monitoring in agriculture; enables low-power, long-range, real-time sensor communication for large-area data.
Medium	Zigbee, mmWave Radar	Zigbee (CSMA/CA for collision avoidance), Custom Radar Protocols	CSMA/CA, TDMA (Time Division)	AES-128, TLS, IPSec	Low power, Low latency, Medium throughput	Real-time field data collection, motion detection, and smart irrigation; ensures reliable, low-latency communication.
Short	Bluetooth, Wi-Fi, RFID	Bluetooth (Frequency hopping for collision avoidance), Wi-Fi (CSMA/CA), ISO 18000 (for RFID)	FHSS (Frequency Hopping), CSMA/CA	AES, WPA2, EAP, TLS	Low to medium power, Low latency, High throughput (Wi-Fi), Medium throughput (Bluetooth)	High-speed, low-latency data exchange for healthcare, asset tracking, and environmental monitoring; real-time decision-making in localized areas.

3.3.2. Location-Aware Systems

Location awareness is necessary for Precision Farming (PF) tasks that have significant spatiotemporal, environmental, public health, and food safety consequences [48]. Utilizing technologies like GPS, GIS, and remote sensing, location-aware systems are essential for improving agricultural practices because they enable accurate data collection and analysis in specific geographic regions. These technologies make it easier to optimize several farming procedures, such as crop monitoring, pesticide application, and irrigation management, which improves sustainability and efficiency [40,49,50]. GPS is widely used to map agricultural fields, track farm equipment, and assist Variable Rate Technology (VRT) systems that guarantee precise fertilizer and seed delivery [39,51]. By producing comprehensive maps of farms and offering spatial analysis of soil, crop yields, and pest distribution, GIS systems provide a substantial contribution to better informed farm management choices [40]. In other scenarios, such as GPS-guided routes or VART that can tolerate low data communication latencies, unmanned ground vehicles present strict deadlines; however, hotspots in agriculture, such as drought land or low- or high-temperature zones localized by GPS, GIS, or remote sensing systems, must be served immediately because they necessitate meeting strict deadlines. The impact on agricultural operations is negligible despite these minor delays. On the other hand, changes to GIS maps, cropping schedules, or satellite imaging trends for the upcoming collection of spatial data offer flexible tasks with only loose deadlines.

Core Technologies

In order to make well-informed farm management decisions, precision agriculture makes extensive use of remote sensing technologies, such as satellite imagery, UAVs, and proximity sensors, which offer real-time data on crop health, soil moisture, and environmental conditions [41,42,52]. Because radio-frequency identification (RFID) enables the precise tracking of assets and livestock, it enhances agricultural output. High-resolution three-dimensional maps of agricultural landscapes are produced using Light Detection and Ranging (LIDAR), enabling a thorough evaluation of crop development and environmental factors [44,45,53]. By providing non-destructive plant health monitoring, identifying water stress, nutritional shortages, and pest infestations, and enabling prompt actions to maximize agricultural production, terahertz (THz) technology enhances precision agriculture [46,54–56]. Table 4 shows the frequency range and its effects on the method of wireless power transfer, with LF and HF utilizing inductive coupling (for shorter ranges) and UHF using electromagnetic waves (for longer ranges).

Farming is anticipated to be greatly improved by extended reality (XR) for virtual field inspections, artificial intelligence (AI) for autonomous job execution, blockchain for improved data administration and security, 6G for real-time data transfer, and Agriculture 5.0. These technologies are expected to improve farming sustainability and efficiency, guarantee regulatory compliance, and encourage equitable technology adoption [5,57].

In situations where harvesting or intervention must be started immediately, such as fruit maturity monitoring or sudden crop stress, instantaneous THz signal processing is required. Periodic real-time analysis that addresses tight deadlines, like mapping soil nutrients, allows corrective fertilization to be done within an ideal timeframe. Soft deadlines, such as seasonal quality assessment or long-term trend monitoring, rely on continuous data logging without exact scheduling. By ensuring that critical tasks are finished on schedule while non-urgent activities have flexibility, this integration optimizes crop productivity and operational efficiency.

Table 4. Frequency spectrum allocation for RFID devices [44].

Frequency Band	Operating Frequency	Typical Read Range	Key Features
Low Frequency (LF)	120–134 kHz	∼10 cm	Short range, slower speed, less affected by metal/liquids
High Frequency (HF)	13.56 MHz	Up to 1 m	Common in access control, libraries, and payments
Ultra High Frequency (UHF)	865–868 MHz (EU), 902–928 MHz (USA), 865–867 MHz (India), 920–926 MHz (Australia), 952–954 MHz (Japan), 902–907 MHz & 915–928 MHz (Brazil)	Up to 10 m or more	Fast, affordable, widely used in logistics and inventory
Very High Frequency (VHF)	30–300 MHz	Varies	Used for specific applications like vehicle tracking

3.3.3. Mobile Software Apps

Mobile applications are critical to precision agriculture because of their real-time data collection and analysis capabilities. These apps provide data to cloud platforms for analysis after collecting data from sensors such as GPS, temperature, and soil moisture. They use machine learning and strong data analytics to help farmers make smart crop management

decisions. Remote monitoring is made possible by the apps, which offer insightful information about agricultural output and livestock health. They also communicate with other technologies, such as UAVs and IoT sensors, to provide full farm management assistance. Because of the user-friendly design, farmers can easily understand data to optimize resource allocation and boost crop yields.

Real-time systems for use in mobile apps enable deadline-driven sensing, inference, and actuation. Such characteristics are essential, as agronomic decisions are tightly coupled to temporal environmental dynamics. Real-time monitoring pipelines guarantee bounded latency for ingesting soil moisture, microclimate, and imagery data. Real-time monitoring allows controlled irrigation scheduling or frost mitigation, triggering within agronomically valid time windows rather than after batch-processing delays. Algorithms for real-time control can adjust parameters like picture resolution, inference time, workload, or sensor samples in response to operating environment-imposed battery limitations, CPU or GPU demands, or even thermal throttling. As such, real-time systems' deadline-aware scheduling guarantees that camera-based crop stress or disease inference procedures run as planned and without interrupting user interface or sensor acquisition threads. With a predefined end-to-end delay, network-aware real-time algorithms prioritize and transmit essential alerts—like sudden changes in evapotranspiration or abnormalities in sensors—under sporadic rural connectivity. With real-time anomaly detection on streaming data, defects or the spread of stress may also be identified by observing unexpected shifts in soil or plant health parameters early enough. Agricultural mobile applications implementing real-time methods apparently become closed-loop, deterministic cyber-physical systems that improve responsiveness, energy efficiency, and the reliability of decisions made in dynamic field environments.

3.3.4. Autonomous Systems

Robotic systems, including Unmanned Aerial Vehicles (UAVs) and AI-driven devices, enhance agricultural efficiency by automating processes such as planting, harvesting, and crop monitoring (see Table 5). AI is used for activities, such as planting and plowing by autonomous tractors like CNH Industrial's model [58]. Computer vision is used by robots, as the AI-powered weed-scanning machine [59], to recognize and eliminate weeds. Autonomous UAVs are becoming increasingly popular for crop health monitoring, as sensors detect stress and nutrient deficiencies. Likewise, cooperative robots (cobots) offer support for repetitive, physically demanding, potentially hazardous, and labor-intensive jobs, while human intelligence guides the critical thinking of customized logic. Cobots [60] have been deemed essential to Agriculture 5.0 and as an effective tool for raising productivity while encouraging prospective farmers to opt for careers in agriculture in lieu of unprofitable or oversaturated sectors. The UAVs provide real-time data for targeted resource application, improving farming practices and reducing pesticide usage [61]. UAVs can gather information about crops and agriculture, including aerial photos, as shown in Figure 4. This information is utilized to identify possible issues like insect infestations or nutritional deficiencies and to enhance farming practices. In precision agriculture, drones have become indispensable because they give farmers high-resolution photos of their crops. The types of UAVs used in precision agriculture are summarized in Table 6. While sensors and cameras gather information on physiological parameters like leaf area index, chlorophyll content, and biomass, UAVs assist in real-time monitoring of plant health and growth trends. Trends and patterns in data are next found with machine learning techniques. UAVs using thermal and multispectral sensors can identify plant stress before it manifests itself, averting output losses.

Case Study: Crop Monitoring Using UAVs in Indian Rice Farms–The Indian Agricultural Research Institute (IARI) investigated the use of UAVs with multispectral sensors to track nitrogen levels in rice fields in a pilot project [62]. Crop output increased by 15% and nitrogen usage efficiency improved by 25% as a result of the research. Additionally, it decreased reliance on physical labor at crucial stages of crop growth. The potential of UAV-enabled precision agriculture to improve nutrient management and encourage sustainable practices on smallholder farms is demonstrated in this case study.

Table 5. Examples of agricultural robots: purpose, features, and impact.

Ref.	Robot	Purpose	Key Features	Capacity/Impact
[63]	HV-100 (Harvest Automation)	Strawberry Harvesting	Vision system, Robotic arm, Adaptive software	Harvests 14,000 pounds/day, reduces labour costs and fruit damage
[64]	FD20 (FarmDroid)	Seeding and Weeding	Solar-powered, GPS navigation, weeding	Covers 6.5 ha/16 acres, promotes sustainable farming
[65]	See & Spray (Blue River Technology)	Targeted Herbicide Application	Computer vision, machine learning, precision spraying	Minimizes pesticide usage, 96 hectares in 24 h reduces environmental impact
[66]	ARA (EcoRobotix)	Weeding for Fruit and Vegetables	Solar-powered, computer vision, mechanical weeding tools	Efficient and precise weed removal, 4 hectares/hour, day and night, reduces labor
[67]	Naïo–OZ	Hoeing, Weeding, and Seeding	Electric-powered, computer vision, weeding tools	Efficient and precise weed removal, 1000^2 m/h, reduces labour
[68]	AGX (Clearpath Robotics)	Customisable Agricultural Robotics	Modular base, LiDAR, cameras, GPS	Supports various tasks like data collection, crop monitoring 0.1 hectares/hour

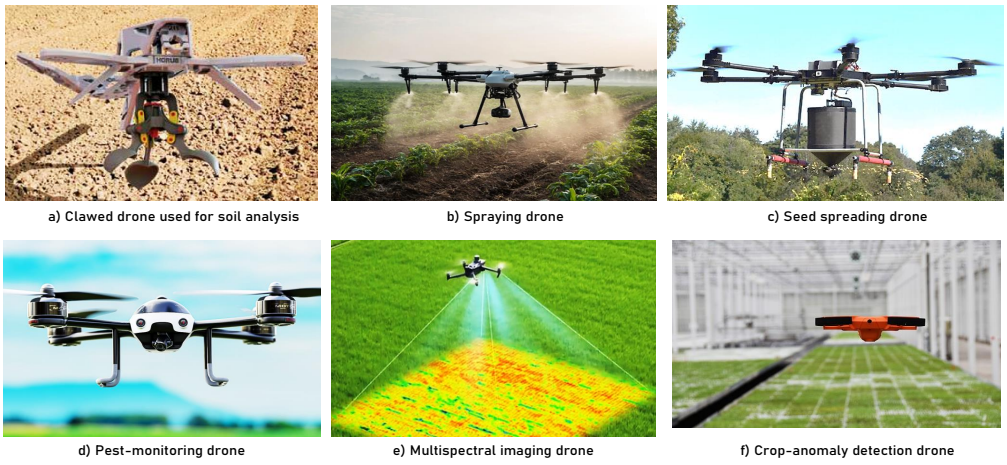


Figure 4. Aerial drone types in precision agriculture [69–74].

Table 6. Different types of drone technologies for use in agriculture.

Drone Type	Characteristics	Applications	Key Features
Fixed-Wing Drones	Long endurance, covers large areas, GIS sensors	Large-scale field monitoring	Remote Sensing: Captures crop health, soil moisture, topography. Spatial Analysis: Monitors crop conditions, disease.
Rotary-Wing Drones	Vertical take-off, highly maneuverable, ideal for irregular terrains	Small farms, detailed crop inspections	Precision Agriculture: Maps soil, moisture, crop health. Data Visualization: Displays data in maps, charts.

Table 6. *Cont.*

Drone Type	Characteristics	Applications	Key Features
Hybrid Drones	Combines vertical take-off with fixed-wing efficiency	Large farms with varied terrain	Remote Sensing: Multiple sensor types for data collection. Precision Agriculture: Site-specific management.
VTOL Drones	Vertical take-off, transitions to fixed-wing flight	Combines agility and endurance	Data Visualization: Visualizes complex data. Spatial Analysis: Optimizes resource allocation.

3.3.5. Edge Computing

Precision agriculture is changing due to edge computing, which processes data close to its source, lowers latency, and boosts productivity. Edge computing, which has its roots in content delivery networks [75,76], tackles issues with IoT and big datasets by providing advantages like decreased latency and cheaper bandwidth costs. It helps farmers make timely decisions by enabling real-time analysis of environmental, livestock, and crop data. By lowering reliance on centralized clouds and enabling offline capability in remote locations, this technology also reduces bandwidth constraints, making it essential to contemporary agricultural operations [77]. Use cases span retail, smart cities, manufacturing, and healthcare. With GPUs, BlueField Data Processing Units, and management tools like NVIDIA Fleet Command, NVIDIA is essential. Global edge expenditure is expected to reach 378 billion in 2028 [78]. The development of AI, IoT, and 5G will further propel the adoption of edge computing, extending use cases beyond visual AI to include robotics, natural language processing, and recommender systems.

3.3.6. Digital Twins

A virtual representation of an actual item that is updated in real time by sensors and analytics is called a digital twin [79]. Using technologies like wireless sensor networks (WSNs), the Internet of Things (IoT), and machine learning, digital twins in agriculture monitor and improve processes including soil conditions, crop growth, machinery performance, and animal health (see Figure 5). To enhance sustainability, productivity, and decision-making, these technologies offer real-time data, predictive analytics, and simulations. By improving irrigation, soil management, machinery maintenance, and pest control, they tackle the difficulties of contemporary farming, such as erratic weather and resource limitations. This results in reduced waste, improved productivity, and better resource utilization, enhancing resilience and environmental sustainability.

A spatial digital twin (SDT) focuses on geospatial data for better spatial context [42]. It incorporates precise location and dimensional data, with the SDT market projected to reach $25 billion due to advancements in spatial technologies, AI, and ML. The SDT development involves a five-layer approach: (1) data acquisition and processing, (2) data integration and metadata management, (3) data modeling and big data analytics, (4) GIS software, maps, and APIs, and (5) key components for visualization, querying, simulation, and prediction. AI/ML, blockchain, and cloud computing enhance SDTs, but computing platforms are fundamental to ensuring the accuracy and precision of data and results.

3.4. Tasks and Scheduled Completion

Hard deadline tasks–Crop loss or operational failure persists if hard deadlines are not met. Real-time systems assign high priority to tasks or events that demand it to ensure their timely completion. 5G or 6G networks support ultra-low latency data communications, in particular live streaming of data and information exchanges. Tasks like routinely watering areas or using UAVs or UGVs to spray pesticides are prioritized by

edge computing. WSNs continuously monitor and identify disease outbreaks, while THz technology evaluates the maturity of produce. Real-time decision-making is made possible by the virtualization of physical processes through smartphone apps and digital twins. GPS/GIS-enabled autonomous systems require high-speed task scheduling and management to ensure highly accurate localization and hotspot identification at high speeds, and UAVs/UGVs require precision sensing and detection algorithms that demand high-performance computing and multi-processing with hard deadlines. To safeguard crop output and operational efficiency, real-time solutions prevent delays and ensure that critical irrigation, pest control, or harvesting operations occur precisely on schedule.

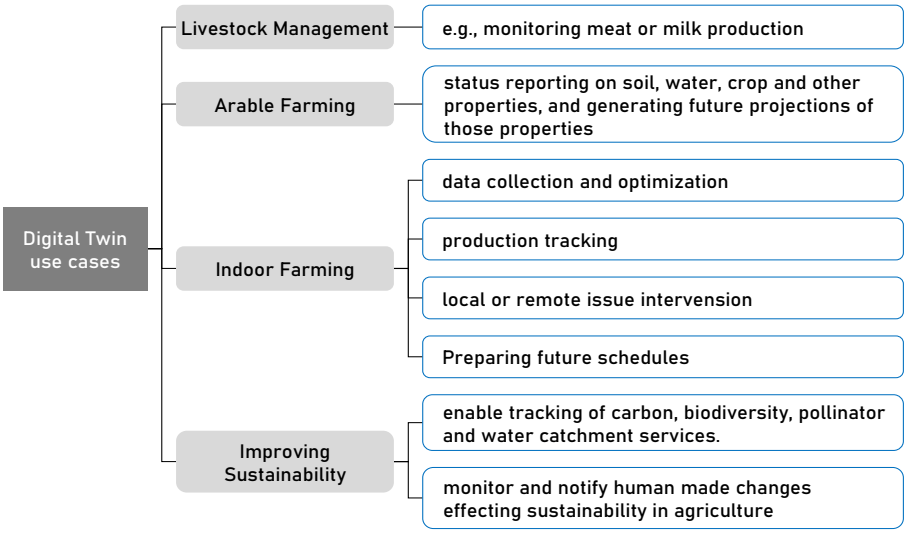


Figure 5. Example use cases—digital twin in precision agriculture [80].

Firm deadline tasks–Some tasks are time-sensitive; however, minor delays are permitted. Real-time approaches employ dynamic scheduling, where jobs with medium importance are given a fair amount of time to complete without taking precedence over those with strict deadlines. THz soil nutrient mapping, GPS-guided UAV aerial surveys, and regular irrigation utilizing WSN-guided scheduled fertilizing can all tolerate short delays; however, these can still achieve operational efficiency targets. While edge computing makes sure that local processing lowers latency, AI recommendations, XR-assisted field activities, and VRT apps are scheduled according to resource availability and time criticality. Multiple firm-deadline jobs can run simultaneously without interfering with hard-deadline processes thanks to real-time monitoring, which guarantees that bandwidth requirements are satisfied.

Soft deadline tasks–Soft deadlines include tasks such as planning, data analysis, and non-urgent monitoring tasks. Real-time systems lower the priority of certain tasks to ensure high-priority tasks are completed first. Task prioritization ensures that critical procedures are never delayed or interrupted. AI-based long-term yield forecasts, digital twin simulations, RFID inventory monitoring, UAV field surveys, seasonal crop quality evaluation using THz, GIS map updates, and soil quality assessments are a few examples of soft deadline tasks. These kinds of tasks leverage available bandwidth and compute power; however, they do so without interrupting with high priority tasks or events. Soft deadline tasks such as adaptive task priority assignment, predictive scheduling, and continued data logging based on real-time scheduling methods responsive to higher-priority agricultural operations while supporting strategic planning.

3.5. Sensing and Analysis

3.5.1. Physical State Recognition

Precision agriculture can leverage different models to assess and interpret the health status of fruits and vegetables. These models give vital insights into the quality, freshness, and nutritional worth of agricultural products by analyzing sensory inputs, including vision and sound. Developments in machine learning and data analytics drive them. Image Analysis-based Models–AI models virtually sense spoilage signs, such as discoloration, decay, or mold growth by analyzing images of fruits and vegetables. Similarly, Sensory Analysis-based Models–can monitor variables, such as temperature, humidity, and pressure to detect deterioration and spoilage. Models based on biochemical analysis are used to identify indicators of spoilage; they measure variations in pH, sugar concentration, and volatile organic compounds. A more thorough understanding of the physical condition of horticultural crops can be attained by combining these methods.

3.5.2. Image Analysis

In the context of intelligent external trait detection, image-based analysis typically follows a structured workflow consisting of (i) image acquisition (e.g., RGB or hyperspectral imaging), (ii) preprocessing and normalization, (iii) segmentation to isolate plant organs or canopy components, (iv) feature extraction based on color distribution, texture metrics, spectral signatures, and morphological descriptors, and (v) classification using convolutional neural network (CNN)-based deep learning models [81–83]. These approaches enable the detection and classification of visually and spectrally observable plant traits, including disease symptoms, nutrient deficiencies, water-related stress indicators, morphological variation, and phenological stages. Figure 6 shows a typical process of semantic segmentation applied on video frames capturing crop products or livestock. Image analysis supports the categorization of spoilage, pests, and diseases by providing non-invasive monitoring of crop characteristics such as size, texture, and color [81,82].

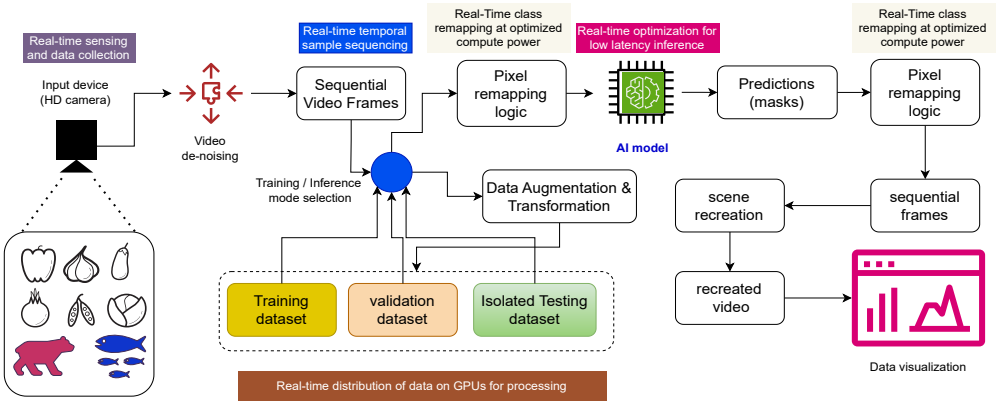


Figure 6. Live stream processing with AI automation based on semantic segmentation for use in precision agriculture.

Deep learning and segmentation are two methods that improve detection accuracy. Biological signals and interior structures can be acquired with advanced modalities that include hyperspectral imaging, Raman, near-infrared (NIR), X-ray, magnetic resonance imaging (MRI), UV fluorescence, and time-domain imaging. As shown in Figure 7, the process occurs in three levels: low-level processing (image acquisition and preprocessing), intermediate processing (image segmentation, feature extraction), and high-level processing (recognition, interpretation, and classification) [83–85]. Emerging approaches, including generative adversarial networks (GANs) and anomaly detection, address data scarcity;

however, approaches are expensive with low portability and high computational demand, thereby imposing limits on large-scale adoption of these technologies [27].

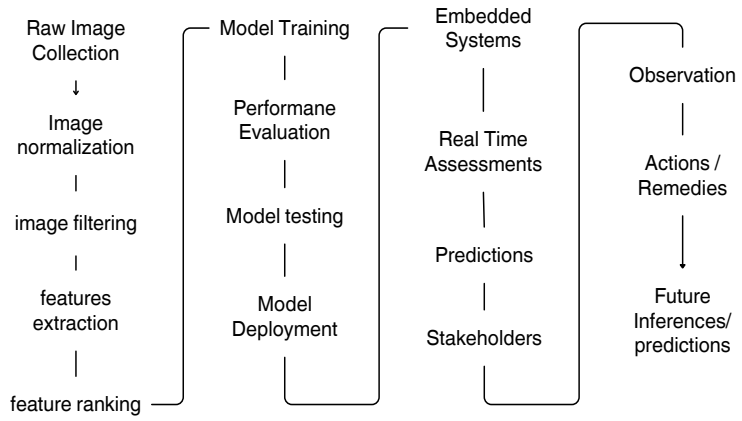


Figure 7. Overall view of AI-based imaged processing pipeline for classification and object detection in precision agriculture.

3.5.3. Sensory Analysis

Sensors can capture real-time environmental and physiological parameters in agriculture. In horticulture, attributes such as appearance, aroma, and flavor are central to quality assessment. Electronic and optical sensors (gas sensors, biosensors, and electronic noses) are adopted to monitor these attributes by detecting VOCs linked to early spoilage in commodities like apples and bananas (Figure 8). Likewise, UAVs or vehicle-mounted optical sensors can estimate soil texture, moisture, and plant vigor through reflectance measurements when deployed in managing post-harvest practices [86]. Electrochemical sensors, including ion-selective electrodes, allow precise quantification of pH and nutrient availability [87]. Collectively, these tools enable early stress detection, optimize storage, and reduce food loss.

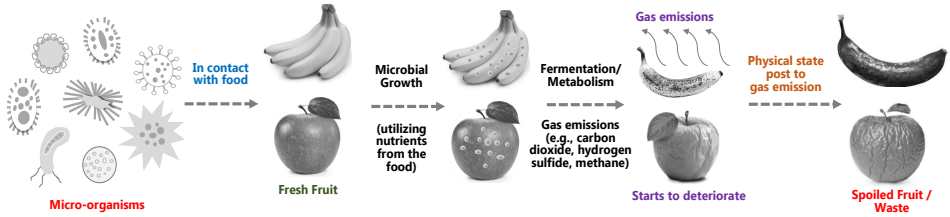


Figure 8. Micro-organisms cause fruit spoilage and produce gas emissions.

3.5.4. Biochemical Analysis

The identification of external traits is improved by biochemical sensing, which links reflectance-based signals to the physiological mechanisms that cause visible plant responses. Metrics such as pH, soluble sugars, or nutritional balance are often measured internally; however, these are often linked to externally noticeable characteristics, such as color shifts. Stress-induced color shifts, canopy reflectance changes, and morphological changes are examples of externally visible traits that are often linked to internal measurements like pH, soluble sugars, or nutritional balance.

These days, electrochemical and nano-enabled biosensors [88,89], can be employed to calibrate or validate indications acquired from pictures, allowing real-time tracking of metabolites and nutrient flows. On the other hand, spectroscopic techniques such as Raman and NIR are not only used to quantify composition; they also enable the non-

destructive assessment of stress before obvious visual signs appear by using changes in spectral fingerprints to infer metabolic state.

Instead of working alone, biochemical analysis strengthens external trait detection frameworks by improving model interpretation and reliability. These techniques are being utilized more and more as a validation layer in integrated real-time precision systems, despite the fact that they still have practical limitations, particularly with regard to field deployment, cost, and calibration.

3.5.5. Case Study: Remote Sensing in Maize–PGC Intercropping Systems

Conventional maize (*Zea mays* L.) production in the U.S. Corn Belt is linked to water pollution, erosion, and nutrient losses [90,91]. Researchers in Iowa are experimenting with intercropping maize with cool-season perennial ground covers (PGCs), which offer several agronomic advantages and year-round live cover, to increase system resilience [92]. UAV-based hyperspectral sensing was adopted to evaluate the performance of this system, providing high-resolution monitoring of canopy physiology and plant–plant interactions.

Certain PGCs develop dense, shallow fibrous root systems and thrive in cool, moist environments [93]. When combined with robust winter survival, they create a living mulch that holds onto water and absorbs nutrients like N, P, and K that would otherwise be lost in traditional systems [94]. Subsequent seasons may see an increase in maize output as these nutrients are progressively mineralized and returned to the soil [91]. PGCs' role in water retention and nutrient cycling was validated by UAV-based vegetation index research, which revealed that they maintained higher Normalized Difference Water Index (NDWI) [95] values during colder, wetter circumstances. The Normalized Difference Water Index was calculated by Equation (1):

$$\text{NDWI} = \frac{\rho(\lambda_{560}) - \rho(\lambda_{840})}{\rho(\lambda_{560}) + \rho(\lambda_{840})} \quad (1)$$

where $\rho(\lambda_{560})$ and $\rho(\lambda_{840})$ represent the spectral reflectance measured at wavelengths centered at 560 nm (green band) and 840 nm (near-infrared band), respectively. Higher NDWI values indicate greater vegetation water content and improved canopy moisture status. PGC integration reduced soil organic carbon (10.1%) and N losses (6.5%) while increasing soil potential mineralizable N by 8.5% when compared with standard maize systems [94]. The resolution required to spatially map these impacts throughout the field was made possible by remote sensing techniques, underscoring the accuracy benefit of UAV-based surveillance.

To separate PGC pixels from maize, NDWI was used as a spectral mask. A further key methodological step is to apply extra vegetative indices that are typically used for maize to the PGC after it has been isolated. In comparison to traditional maize systems, erosion was decreased by 90% and runoff by 60%, demonstrating conservation advantages [96]. The accuracy of system evaluation was improved by the spatially precise maps of these impacts supplied by UAV-based chlorophyll and water-related indicators (CI, CIRE, NDWI, and NDRE). The mathematical formulations of CI, CIRE, and NDRE follow standard spectral reflectance-based definitions reported in the literature [97–99].

Importantly, the intercropped system also affects maize performance through light competition. The presence of PGC modifies the red/far-red light environment, triggering the shade avoidance response (SAR) in maize during early growth stages [91]. The red to far-red ratio (R/FR) was calculated by Equation (2):

$$\text{R/FR} = \frac{\rho(\lambda_{670})}{\rho(\lambda_{730})} \quad (2)$$

where $\rho(\lambda_{670})$ and $\rho(\lambda_{730})$ represent the spectral reflectance measured at wavelengths centered at 670 nm (red band) and 730 nm (far-red band), respectively. The R/FR ratio is commonly used to assess canopy light quality and phytochrome-mediated plant responses, particularly under competitive or shaded conditions. Localized SAR hotspots were identified by UAV-based red/far-red ratio mapping (Figure 9), where maize changed carbon allocation to stem elongation at the expense of root development, eventually penalizing production. This application shows how hyperspectral sensors can record indirect stress responses in maize in addition to evaluating PGC health. UAV-based hyperspectral imaging provides an unparalleled view into the dynamics of intercropped systems by using NDWI to isolate PGC pixels and then applying maize-adapted vegetation indices to both components. The composite Figure 10, which displays the orthomosaic RGB of the intercropped field and exhibits NDWI-based differentiation and PGC discrimination, summarizes preliminary findings. Our findings together show how precise regulation of maize–PGC intercropped systems using sophisticated remote sensing might improve water and nutrient use efficiency while preserving long-term sustainability.

UAV-based hyperspectral imaging allows for the spatial categorization and quantification of observable canopy characteristics in maize–PGC intercropping systems from the standpoint of external trait detection. Integrating image-based trait extraction and precision monitoring is proven by high spatial resolution mapping and detection of water-status indicators (NDWI), light-quality responses linked to shade avoidance (R/FR), and canopy-level morphological differentiation between perennial ground cover components and maize components.

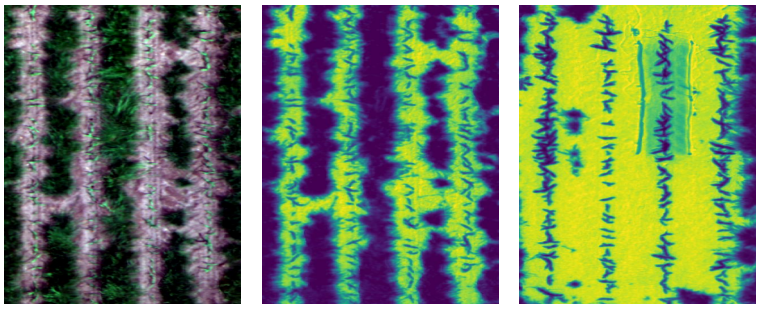


Figure 9. UAV-based hyperspectral analysis of the red/far-red (R/FR) vegetation index in the maize–PGC intercropping system: (**left** image) orthomosaic RGB image of the experimental field; (**center** image) R/FR ratio applied to detect shade avoidance responses (SAR) in maize during early growth; and (**right** image) field-installed far-red (730 nm) lighting used to artificially induce SAR, isolating light-quality effects and enabling assessment of carbon allocation impacts on total biomass and grain yield.

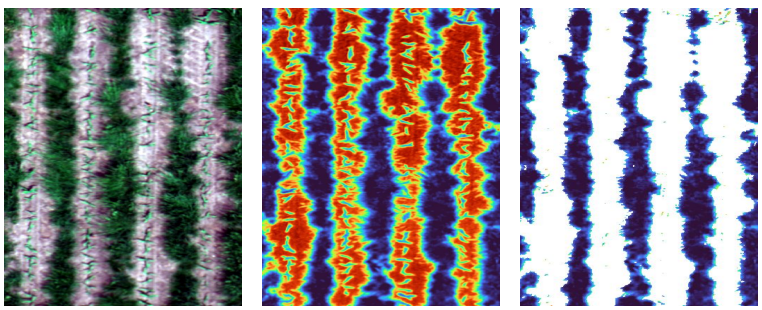


Figure 10. UAV-based hyperspectral analysis of the Normalized Difference Water Index (NDWI) in the maize–PGC intercropping system: (**left** image) orthomosaic RGB image of the experimental field; (**center** image) NDWI applied to the canopy, highlighting spatial variation in water content; and (**right** image) NDWI used as a spectral mask to discriminate PGC pixels from maize, enabling subsequent calculation of vegetation indexes specifically for PGC.

3.6. AI and Data Communications

3.6.1. Artificial Intelligence

Machine learning can boost agricultural productivity by optimizing planting, resource management, and crop growth. Autonomous farming helps reduce labor costs and improve operational efficiency [75]. Convolutional Neural Networks (CNNs) are used to detect diseases and estimate yields, whereas transformer models predict weather patterns and analyze soil health [81,100]. Recurrent Neural Networks (RNNs) with time-series decision-making ability enable forecasts of irrigation requirements, while Decision Trees can handle yield and pest predictions. Generative Adversarial Networks (GANs) enable augmenting datasets in scenarios where datasets pose a significant challenge due to deep AI models requiring large datasets for training to improve generalization. GAN AI models can integrate with Decision Support Systems (DSS) to provide actionable recommendations for agricultural practices. Simulated dataset-based models enable researchers and farmers to test and develop strategies without incurring the costs associated with field trials. High-performance computing (HPC) systems manage large datasets and model complexity, while energy-efficient edge devices enable real-time monitoring. Enabling support for AI models, distributed AI systems can combine edge processing for low-latency tasks with cloud computing for large-scale analysis, ensuring scalability, efficiency, and sustainability in modern agriculture.

Tables 7 and 8 highlight machine vision systems that detect pests, nutrient deficits, and diseases from crop photos. These AI models can analyze data collected with sensors monitoring soil moisture, temperature, or humidity to improve farming techniques and increase productivity. The expansion of the machine-learning market indicates a promising future for AI in the agricultural sector. AI's major role in agriculture is envisioned in (a) Yield Prediction, wherein AI models will forecast crop yields based on weather, soil, and irrigation; (b) Disease Detection, wherein an early crop disease detection can lower losses incurred in medication and fertilization; (c) Soil Analysis, wherein AI will evaluate soil data for fertilizer and treatment recommendations; (d) Autonomous Farming, wherein UAVs and robots will perform planting and harvesting tasks independently, reducing labor expenses; and (e) Optimized Resource Management, whereby AI can predict soil and weather conditions, and allow budget estimations that maximize nutrient utilization and lower waste outcomes.

Table 7. State-of-the-art work demonstrating the use of AI for image processing in precision agriculture.

Ref.	Fruit Name	Task	Key Features	Model	Accuracy
[43]	Apple	Fruit detection and counting	High-resolution video frames, synchronization of UAV cameras, image quality optimization	AI, deep learning, UAV-based multi-camera system	86.8% mean average precision
[101]	Strawberry	Fruit detection	YOLOStrawberry network with Conv_Maxpool, Shuffle_Block, ResNet, SElayer, SPPF backbone, FPN neck	Modified YOLOv5 architecture	89.7% average precision
[102]	Apple	Fruit ripeness classification	Fruit peel characteristics	YOLOv8 and CenterNet models	99.5%
[103]	Palm fruit bunch (PFB)	Ripeness detection	Color constancy model, spectra-based image correction, hybrid color correction	YOLOv8	89.7% mean Average Precision (mAP)
[104]	Blackberry	Ripeness detection	Visual and near-infrared spectral filters, skin texture	Multi-input convolutional neural network (CNN) ensemble classifier	95.1% on unseen sets, 90.2% in-field conditions

Table 8. Weed detection approaches based on machine learning and artificial intelligence.

Ref.	Weed Type	Feature Type	Method	Performance Indices
[105]	Soybean weeds	Drone imagery (Ghost Convolution, BottleNeckCSP, ECA)	Customized model with modified backbone, Ghost Convolution, BottleNeckCSP, ECA layers	Precision = 72.5%, Recall = 68.0%, mAP@0.5 = 73.9
[106]	Lettuce intra-row weeds	YOLOv7 with ECA, CA, ELAN-B3, DownC modules	Multimodule-YOLOv7-L, intra-row weed severity classifier	Precision = 97.5%, Recall = 95.7%, mAP@0.5 = 97.1%, F1 = 96.6%, FPS = 37.3, 100% accuracy in 8 scenarios
[107]	Charlock mustard, creeping thistle, forking larkspur	YOLOv5 (nano, small, medium, large, xlarge)	YOLOv5 for weed detection in wheat fields	Precision: Charlock mustard = 0.96 (seedling), 0.81 (fruit); Creeping thistle = 0.87–0.96; Forking larkspur = 0.45–0.93; YOLOv5 small model precision = 0.86
[108]	Weed growing in cabbage	YOLOv5 and YOLOv8 for weed/crop detection	Direct and indirect weed detection using YOLO models	YOLOv5 Crop: Precision = 0.986, Recall = 0.979, F1 = 0.982; YOLOv8 Crop: Precision = 0.973, Recall = 0.985, F1 = 0.979; Weed detection (both): Precision, recall, F1 < 0.891
[109]	Weed growing in potato	CNN-based image comparison	CNN model for weed detection, resized images for efficiency	Trained on 1300 images (737 weed, 563 non-weed); Model identified weeds and non-weeds with 96% accuracy
[110]	Hoary Cress, Flixweed	Color images	Xception-based deep learning, transfer learning	Best model: 100% accuracy, loss = 0.41, Precision = Recall = F1 = 100%; Second model: 95% accuracy, precision = 91–100%, recall = 88–100%, F1 = 91–96%
[111]	Soybean seedlings	Image-based weed detection	Enhanced YOLOv5, CrissCross Optimization (CCO)	Average accuracy = 98%, 3.94% improvement over traditional models

Agriculture systems with hard, firm, or soft deadlines as outlined by biological attributes, conveyor flow, and other machinery operational speeds during pre- and post-harvesting processes can severely impact latency bounds that guide the selection of AI models for driving precision agriculture systems. As a constrained optimization problem, real-time systems can guarantee to maximize the accuracy of the external trait detection system or devices while guaranteeing their worst-case execution time to be lower than the set deadlines. As such, AI models, for example, CNNs or lightweight YOLO models, can analyze the RGB, multispectral, or thermal images to identify and localize leaf lesions, canopy stress, or even fruit surface defects during pre- or post-harvest operations. Likewise, robotic sprayers, autonomous irrigation systems, UAV-based crop health monitoring, or early disease intervention and prevention systems all require high precision and must satisfy the latency constraints; therefore, they can be envisioned if such deadlines are met precisely. Manual farming practices can cause pest outbreaks, crop dehydration, or excessive use of agrochemicals and therefore may fail to be safety regulations as well as agricultural production necessities.

3.6.2. Explainable AI (XAI)

While AI models allow decision-making in agriculture, their complexity often impedes their adoption by end-users, especially by farmers, for interpreting and trusting the AI-based recommendations [112]. Explainable AI (XAI) provides human-understandable

explanations for AI-generated decisions. The SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) explain models' decision-making outcomes via visualizations of the model learning process and how the models' output relates to predictions, disease detection, or irrigation timing. Incorporating XAI into AI-powered platforms ensures transparency, fosters trust among users, and enhances the adoption of AI tools in farming communities. This trustworthiness is highly desirable, especially when uncovering models' prediction processes since the predictions by the AI models can have a direct impact on human health. As such, the consumption of food and other edible items recommended by AI models to humans needs to be monitored in the future. Essentially, techniques that uncover model learning processes and how models respond to specific inputs hold a high significance when employing AI in precision agriculture. The predictions made by models using input data sensed by WSN also rely on how the employed model learns and responds to such input data. An XAI-based system can explain why an AI model recommends limiting pesticide application on certain crops based on sensor data showing minimal pest activity. Apparently, techniques that reveal how models learn from and respond to sensor input data—such as those gathered via Wireless Sensor Networks (WSNs)—play a critical role in improving both the reliability and ethical use of AI in precision agriculture. This would ensure safer food output and better environmental outcomes. Latency in the explainability of predicted outcomes by models can reduce the level of trust, usability, and safety of AI-based precision agriculture systems. It is necessary to temporally synchronize the development of interpretable model explanations with the AI's decision outputs in order to maintain human-in-the-loop control fidelity, eliminate latency-induced ambiguity, and guarantee deterministic accuracy. Rate Monotonic Scheduling, Earliest Deadline First, Deadline Monotonic Scheduling, Least Laxity First, and Time-Triggered Architecture as deterministic scheduling techniques ensure that periodic, aperiodic, and irregular agricultural activities will meet their worst-case execution deadlines [113–115]. Explainable AI (XAI) supported by high-precision real-time systems can allow human-in-the-loop communication, impose fine latency control, and generate interpretable outputs required by automated processes or human–machine interaction purposes. XAI not only allows inspection of model behaviors but also helps in understanding how the learned models can impact the stakeholders, such as farmers, producers, and consumers. Hybrid and value-based scheduling strategies can be implemented in XAI methods to process tasks generating highly valuable outcomes in precision farming.

3.6.3. Data Communications

Precision agriculture's sustainability heavily relies on the improved connectivity and bandwidth enabled by the 5G and 6G networks since these technologies enable real-time data transmission and analysis, critical for monitoring animal health, farm worker emotions, and crop management [116]. These networks allow remote monitoring, including access to data collected by the sensors and cameras mounted across the farm. In fact, these systems enable support for monitoring farms even in the absence of farm workers, thereby helping farmers to optimize crop yields, water usage, and fertilizer application.

Role of 5G and 6G Networks

5G and 6G networks drive data-driven agriculture by enabling faster and more reliable data transmission that enhances decision-making, resource conservation, and farming efficiency [117]. Wireless communication technologies—such as WiFi, Bluetooth, and cellular networks—track farm equipment and resources in real time. 5G and 6G deliver superior connectivity, higher bandwidth, and remote monitoring capabilities essential for modern precision agriculture. These networks enable improved connectivity, allowing rapid and

efficient data transmission for timely decisions on planting, harvesting, and irrigation. They provide increased bandwidth to support high-resolution imaging and real-time video analysis. Through remote monitoring, farmers can oversee soil moisture, crop growth, and equipment performance from anywhere, identifying issues quickly [52]. 5G and 6G also strengthen precision agriculture by supporting real-time decision-making that optimizes yield, reduces waste, and conserves resources [52]. Furthermore, they empower autonomous vehicles, such as self-driving tractors and UAVs, to operate efficiently and minimize labor costs [116].

3.6.4. Communication Protocols

Local Area Network (LAN) technologies, such as Ethernet and Wi-Fi, offer short-range communication at speeds ranging from 10 Mbps to 10 Gbps and allow short data communication. Metropolitan area networks (MANs) technologies, such as FDDI and ATM, enable networking between cities with data communication speeds ranging from 100 Mbps to 10 Gbps, thus allowing data centers located across cities to communicate agricultural data for analysis. Wide Area Network (WAN) protocols like SD-WAN and MPLS enable global communication at speeds ranging from 1 Mbps to 100 Gbps. WANs allow sharing of data in large platforms, such as research universities or data collection centers, for reporting and analysis at a global level. Essential to the implementation of real-time systems in precision agriculture remains the Controller Area Network (CAN) bus protocol, which is primarily used in real-time and industrial settings, as it is crucial for networking sensors and actuators with minimal configuration [118]. With CANs, electronic control units (ECUs) can exchange data in real-time based on precision agriculture systems, with data transfers of up to 1 Mbps. CAN bus generates differential signaling between the paired CAN_{High} and CAN_{Low} lines. Deterministic communication is crucial for real-time, safety-critical applications such as automotive control systems, industrial process management, and agricultural automation. High-speed data connections that are resistant to noise and other signal impairments are made possible by the paired lines. CAN's collision avoidance prioritizes communications by ensuring the integrity of the system and transmitting any critical data first.

3.7. Primary Challenges

Data management, infrastructural costs, and privacy and security issues are the main obstacles facing precision agriculture. Future research must concentrate on data standardization to ensure accuracy and dependability across farms and regions in order to fully exploit the promise of precision agriculture. Furthermore, further investigation is needed to determine how precision farming may reduce the health risks associated with agricultural pesticides. In order to make data-driven decisions to maximize planting and watering, future research should concentrate on creating instruments and algorithms for evaluating complex data from weather sensors, soil sensors, and satellite imaging. Researchers should also investigate greenhouse gas emissions and eco-friendly practices, such as reducing water and energy use. Advanced precision agriculture technologies and machine learning models are essential to improving forecasts of crop yields, weather patterns, and other agricultural elements. The economic and social effects of precision agriculture, particularly how it might support equitable and sustainable development in rural areas, require more investigation. Precision agriculture has the potential to transform agriculture, enhance healthcare, and promote sustainable development in rural areas by tackling the shortcomings of existing technologies.

Post-flight data processing continues to be a major hindrance to UAV-based site-specific management systems. This restricts the effectiveness of operations and prompt intervention. Inconsistencies in reflectance and motion blur are caused by variations in

factors including sun angle, flight altitude, and platform stability, which frequently call for intensive offline correction. The enormous amount of high-resolution images makes analysis even more difficult, and the spectral similarities between crops and ragweed make proper categorization more difficult. Furthermore, operational restrictions including limited flying time, financial limits, and regulatory complexity all hinder response in changing field circumstances.The absence of fully integrated real-time systems that can detect, correct, and make decisions instantly during UAV operations is the main gap that is highlighted by these problems taken together.

UAV-based control and agricultural sensing encounter a number of significant obstacles. With age, sensors become erratic, resulting in inaccurate calibrations in various soil types. Severe weather conditions seriously impair dependability. Large and noisy datasets make AI analysis difficult since rapid interventions are delayed by the low energy efficiency and poor network connectivity of cellular networks. Additional issues with UAV images that lower data quality include unstable flying circumstances, fluctuating lighting, and motion blur. Moreover, maintaining synchronized, precise, and low-latency data from several sensors and geographical sources may be challenging, particularly for digital twin applications. Large-scale AI/ML analytics also have high computation and scalability needs. Significant operational obstacles are also produced by infrastructure expenses, system responsiveness, and model dependability in dynamic agricultural environments.

Making sure that heterogeneous real-time data from sensors, IoT devices, and geospatial sources is accurate, dependable, and low-latency is one of the problems in developing digital twins and spatial digital twins in agriculture. The quality of the digital twin is greatly impacted by sensor noise, inconsistent data, and synchronization problems, while large-scale geographical data and analytics powered by AI/ML provide significant computing and scaling challenges. The necessity for resilient computer systems retaining accuracy, offering responsiveness, and model dependability under dynamic and unpredictable agricultural situations, infrastructure expenses, and real-time decision needs all contribute to these difficulties.

3.8. Key Limitations

Though there are still many obstacles to overcome, precision agriculture has a lot of potential. Reliable implementation requires thorough, high-quality data, which is frequently lacking for some crops or geographical areas. The requirement for technical know-how restricts accessibility, and high costs discourage uptake, particularly by small farms in low-income nations. Integration problems with traditional systems and ethical concerns like data privacy and animal welfare add to the complexity. Because technologies that work well on small farms might not be suitable for larger businesses or other geographic locations, scalability is still unclear. Effectiveness is also influenced by crop variety, and the lack of uniformity makes system evaluation and implementation more challenging. In order to properly utilize precision agriculture's full potential, several problems must be resolved.

4. Discussion

Despite a number of obstacles, precision agriculture has enormous potential for production and sustainability. Farmers frequently lack the technical know-how and awareness, and governments don't give them enough assistance. To expand the understanding of farmers and policymakers, educational programs are required. The gap between large and small producers may grow as a result of expensive infrastructure costs and specialized solutions, particularly for small-scale farmers who might not be able to afford high-tech solutions. Farmers are discouraged from disclosing sensitive information due to data privacy and security concerns, necessitating precise rules and secure data management. Adoption

is complicated by regional disparities and economic obstacles because small farmers find it difficult to make purchases. In order to encourage greater access, precision agriculture must be incorporated into regional development initiatives that prioritize investments in small-scale farming.

4.1. AI and Machine Learning

There are many obstacles to overcome when implementing machine learning in precision agriculture, such as the requirement for powerful computers, qualified personnel, and safe data storage to guarantee accuracy. Large dataset collection for training is challenging; however, solutions like data augmentation and synthetic data synthesis may result in inconsistent data. The process is made more difficult by real-time needs, which require rapid predictions in order to meet hard or soft deadlines. Inaccurate predictions may have an adverse effect on crop productivity. In precision agriculture, automation continuity requires backup and recovery plans. Applications require real-time evaluations, yet most existing AI-based solutions presume non-real-time systems. Therefore, knowledge gaps, infrastructure constraints, data privacy issues, and financial limitations are significant obstacles to precision agriculture. Stakeholders, technological specialists, and legislators must work together to solve the sector's demands in order to overcome these obstacles. Research on real-time AI systems can increase the productivity and sustainability of precision farming.

4.2. Necessity of Real-Time Systems

In Section 3.3.6, the five technological layer model revolves around real-time embedded systems. They support the digital twin (DT) and spatial digital twin (SDT) frameworks, as do networks, policies, and scheduling. While networks guarantee real-time transmission, embedded devices offer rapid sensor data gathering. Data security and integrity are governed by policies, and model updates and data processing are given priority in scheduling. For accurate simulations and forecasts, these systems are essential for real-time updates in GIS, data integration, and big data analytics. Real-time systems and significant processing capacity are needed for each of the five main technologies: data collection, integration, modeling, GIS, and functional components for visualization and prediction. In order to provide correct representations and update models, real-time systems guarantee the prompt integration and processing of input. For effective digital and spatial digital twin functioning in dynamic, data-driven scenarios, sophisticated computers and real-time technologies are required. Real-time systems and sophisticated computers are essential for efficient digital and spatial digital twin operation in dynamic, data-driven environments.

4.3. Market Growth

IoT and machine learning-driven precision agriculture improves farming efficiency, yield, and productivity. Healthier crops and safer food are the result of these technologies' improvements in crop management, insect detection, irrigation, and supply chain optimization. In these developments, real-time monitoring is essential. By 2032, the precision agriculture market is expected to grow to 55.36 billion dollars [119]. AI is revolutionizing pest control and supply chain management, with the AI market expected to grow from $1.2 billion in 2022 to $10.2 billion by 2032, reflecting a 24.5% compound annual growth rate (CAGR) [120]. While AI improves decision-making through massive datasets, machine learning helps with yield prediction, scheduling optimization, and irrigation management. Agriculture is using predictive analytics at a 15% CAGR [121]. Notwithstanding these developments, real-time evaluations are necessary for other breakthroughs, such as shortening machine learning model inference times, streamlining real-time scheduling and processes, and efficiently allocating resources—all of which are vital for the industry's future.

4.4. Comparison of 4G, 5G, and 6G

The primary areas where 4G, 5G, and 6G diverge in precision agriculture are data handling and real-time UAV or autonomous vehicle operations. 4G supports basic tasks like crop mapping and soil moisture monitoring, but its low bandwidth (100 Mbps downlink, 50 Mbps uplink) and higher latency prevent high-resolution imaging and real-time autonomous operations, limiting its usage to small farms. With lower latency (1 ms) and higher throughput (up to 10 Gbps), 5G improves 4G and makes applications like autonomous UAV fleets, precision irrigation, and high-definition photography possible. It is perfect for large-scale farming because of its increased bandwidth and support for dense device connections, which allow precise fertilization decisions and real-time crop management. By allowing fully autonomous UAV fleets that make real-time changes, 6G further enhances precision agriculture with a latency of less than a millisecond and speeds of up to 100 Gbps. This rapid speed is revolutionizing large-scale, high-tech farming by enabling operations like in-field robots, automated pest identification, and harvest monitoring. Smooth communication between different devices is ensured via massive connections.

4.5. Sensor Systems Market Trends

Due to the growing need for food and grains as well as the growing use of digital and smart agricultural technology, the market for agriculture sensors is anticipated to expand considerably. The need for these technologies is growing as more farmers and producers seek to improve food safety and quality. The agricultural sensor market was estimated to be worth $3599.5 million in 2022 and is expected to rise at a CAGR of 16.12% to reach $7598.6 million by 2027, according to [122]. Furthermore, as illustrated in Figure 11, the global market for remote sensing technology is anticipated to grow at a CAGR of 11.59% from 2025 to 2035, driven by factors such as precision farming, automation in agriculture, and the need for food safety [119]. The market is envisioned to show an increase from $28.36 billion in 2026 to approximately $75.97 billion by 2035.

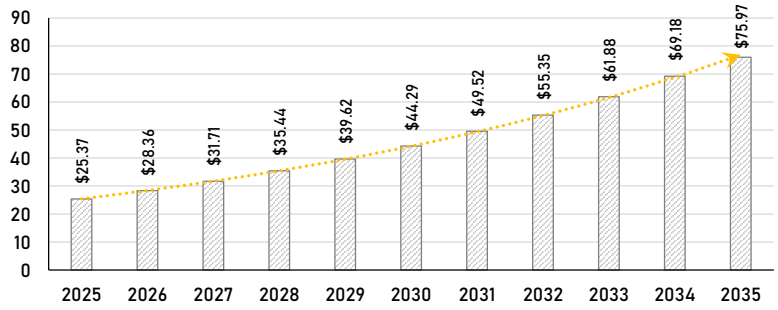


Figure 11. Remote sensing technology market size from 2025 to 2035 (in USD billion) [119].

4.6. Chemical Analysis Trends

Due to significant market expansion leading to rising need for precision agriculture, automation, and food safety technology, the food safety, quality assurance, and sustainability are all significantly impacted by these technologies, and the precision agricultural tech computing industry is predicted to grow, opening up new business prospects. According to [123], the growing demand for fertilizers and crop protection products is expected to propel the worldwide agrochemicals market, which was valued at €227.9 billion in 2022 and is projected to rise at a CAGR of 3.0% from 2023 to 2030. However, there are a number of obstacles to implementing artificial intelligence (AI) in agriculture. Large upfront expenditures impede its adoption and aversion to new technology. Lack of practical experience and poor infrastructure, especially in developing nations, poses a serious concern. AI integration is made more difficult by the lack of rules, privacy issues, and the need for

high-quality data for precise models. To overcome these difficulties, funding, training, gradual adoption, and ongoing research are all required.

4.7. Economic Feasibility and Regional Constraints

Regional variations in economic, legislative, and cultural aspects impact the viability of precision agricultural technology. Even if there are obstacles, innovation and education may aid in removing them and encouraging adoption. Costs play a big role since small farmers in underdeveloped countries could find it difficult to purchase this technology, but huge agribusinesses in rich countries can. Infrastructure is important; in comparison to Africa and Southeast Asia, areas like North America and Europe have more advanced internet and data technologies. Although many emerging regions lack sufficient training opportunities, a trained workforce is required. Adoption may be constrained by privacy laws and conventional farming methods, among other cultural and regulatory differences. Furthermore, the precision and efficacy of precision agricultural systems might be impacted by local climate and environmental factors.

4.8. Implications

Precision farming improves healthcare outcomes and post-harvest procedures. Food security and sustainability are improved by addressing issues including transportation, storage, and processing after harvest in order to preserve food quality and nutritional content. In horticulture, precision farming can lower wastes by tracing and monitoring rotting during storage and transportation using quality detection algorithms. It also forecasts the best periods to harvest, which increases marketability. These technologies improve results and save medical expenses in the healthcare industry by providing individualized dietary recommendations through consumer applications based on health data. They also maximize stock management, guaranteeing resource availability and avoiding delays. Precision agriculture contributes to sustainability by improving food safety, quality assurance, individualized nutrition, and resource management.

4.8.1. Precision Monitoring and Real-Time Systems

Agriculture is greatly advanced by real-time monitoring systems and the Internet of Things, which allow for behavior tracking and plant health analysis. While IoT devices monitor plant health and provide critical data for early disease identification and treatment, automated vehicles, such as ground sprayers, improve pesticide use and fertilizer administration. To ensure prompt treatments, sensor networks must monitor variables, such as soil moisture, temperature, pH, humidity and various other health parameters, with high precision. Hard real-time systems play a critical role in the collection and examination of environmental data in real time. Real-time systems supporting sensor and sensed data simulation are essentially a prerequisite for simulating such real-time sensor behaviors. UAVs and AATVs, as examples of automated equipment driven by AI technologies, help improve productivity, cut down on labor, and lower environmental effects; however, these underscore their significance in sustainable and precision agriculture only if the underlying hard real-time systems can meet the requirements of high precision and accountability prior to deploying them for data collection or to carry out any defined automated agricultural operation. Apparently, the development of real-time systems with extreme high precision is a major challenge currently and in the near future as well since data collection and communication at high speeds (5G or 6G) necessitate high-precision real-time systems to effectively deliver and disseminate both data and information in agricultural systems. Currently, agricultural settings reveal labor shortages because technologies such as satellites or aerial imagery pose technical challenges beyond human capabilities. Unmanned Ground Vehicles (UGVs) and other automated machines primarily intended for ground operation

do not reflect such limitations. In fact, these technologies certainly eliminate costs primarily incurred in the design and development of precision agriculture setups. Nonetheless, UGVs also have high-precision and real-time monitoring requirements, thus necessitating highly efficient real-time algorithms that enable control in real-time applications used in precision agriculture.

4.8.2. Post Harvesting

Precision agriculture technologies can revolutionize post-harvest practices by enhancing crop quality, reducing waste, and improving public health. Sensors in storage facilities and shipping containers monitor conditions like temperature and humidity, ensuring optimal environments for maintaining nutritional value. Data analysis from these sensors enables algorithms to recommend actions that minimize losses and ensure food safety. Additionally, precision agriculture can advance post-harvest processing by identifying optimal methods based on crops' chemical composition. Improved supply chain management through real-time data facilitates efficient logistics, timely communication, and reduced waste, optimizing the food system for better health outcomes and sustainability.

4.8.3. Human Health

Precision agriculture improves food quality, safety, and nutrition by using technology such as Internet of Things (IoT) sensors, UAVs, satellite photos, and machine learning (ML). These technologies provide real-time crop health monitoring by reducing pesticide use and ensuring safer food production. GIS and Variable Rate Technology (VRT) enhance nutrient management, leading to better soil and healthier crops. AI and data analysis boost yield and offer tailored nutrition advice. Furthermore, precision agriculture monitors farm workers' health, improving remote communities' access to healthcare. However, putting these technologies into practice requires technical expertise in data collecting, sensor calibration, and networking protocols.

5. Conclusions

5.1. Key Insights

Precision agriculture has the ability to totally change the agricultural sector by providing comprehensive insights into crop and livestock management. It can improve food safety, environmental sustainability, and human health by raising agricultural yields, enhancing nutritional value, and reducing waste. Big data, machine intelligence, and IoT integration improve animal well-being and lessen their negative effects on the environment. However, additional study is needed in the fields of automation, machine learning, data collection, and greater collaboration between the agriculture and technology sectors.

5.2. Recommendations

5.2.1. Design and Integration Perspective

Adoption of precision agriculture should be encouraged through business and government cooperation, providing incentives and support to increase agricultural yields and sustainability. Advanced software that can handle big datasets is needed to integrate data from several sources (such as soil sensors, weather forecasts, and satellite photography). To guarantee accessibility, especially for farmers with little technological knowledge, user-friendly tools must be created. Adopting precision agriculture successfully requires education, training, and assessment of the economic and environmental effects.

5.2.2. Engineering Perspective

Open-source software may promote innovation by facilitating data sharing amongst farming companies. Real-time monitoring is made possible by IoT connectivity with cloud computing, while cloud platforms provide analytics and storage. UAVs, sensors, and smartphone apps are examples of inexpensive, user-friendly technology that should be given priority. Standardization encourages cooperation by guaranteeing security, privacy, and interoperability. Agriculture will become more productive and sustainable as a result of the integration of edge computing, machine learning, and artificial intelligence.

5.3. Transformation Ahead

Using cutting-edge sensors and technology like GPS tracking, Internet of Things sensors, and smart cameras, precision agriculture revolutionizes farming. Predictive maintenance is made possible by these technologies, which also improve agricultural conditions and save labor costs. But issues like data consistency and moral dilemmas need to be resolved. Ongoing research will improve adoption and solve problems, opening up new job possibilities and stimulating the farm sector's economy. Precision farming has the potential to address important agricultural issues and enhance social well-being.

5.4. Future Directions

In order to improve crop and livestock monitoring and enable early issue diagnosis, future research will concentrate on increasing sensor accuracy and dependability. Health and sustainability will be improved via integration with automation and other cutting-edge technology. Data integration, security, and the intricacies of real-time computing are major obstacles. While ethical standards for data security and animal welfare will guarantee responsible usage, further developments in data analysis and machine learning will allow for more individualized treatment. Agriculture will continue to change as a result of these advancements.

Future studies will concentrate on creating 5G/6G technology's ultra-low latency and high bandwidth capabilities. To enable simultaneous sensor data collection, actuator control, UAV and UGV imagery, monitoring and control, and transmission of live streaming data over long distances while guaranteeing low latency constraints, sensor networks would require highly effective dynamic task scheduling algorithms. Motion-blur compensation, multi-sensor data fusion from hyperspectral, multispectral, and soil sensors, and edge-based computing to enable data processing locally and reduce dependence on cloud servers are examples of how to manage such jobs in the field. However, one major concern underlying the significance of these technologies is the timing and efficiency of scheduling mechanisms and optimization, which primarily relies on the implementation of real-time algorithms and optimization methods for disseminating available resources. Real-time systems, hence, serve as a backbone to precision agriculture and emphasize highly concentrated research compared to any other sub-domain of precision agriculture.

Precision Agriculture for Climate Resilience

Precision agriculture could be the backbone supporting technology enabling the boosting of farming systems' resilience in light of the climate's growing unpredictability. Proactive agricultural methods can benefit from technologies like weather-linked crop modeling, early warning systems for drought, and predictive analytics for insect outbreaks. Farmers in semi-arid regions can improve irrigation planning by combining satellite-based rainfall forecasts with real-time soil moisture data. Similarly, AI-enabled systems may recommend strong agricultural varieties that match regional weather trends.

These techniques safeguard crops while encouraging sustainable adaptability to shifting climatic circumstances.

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