Precision Agriculture Smart Farming and AI in Agriculture: A Survey

www.surveyx.cn

Abstract

Precision agriculture, smart farming, and artificial intelligence (AI) are revolutionizing modern agriculture by integrating advanced technologies to enhance productivity, sustainability, and resource management. This survey provides a comprehensive overview of these practices, emphasizing their role in addressing global agricultural challenges. The paper is structured to cover core concepts, technological advancements, applications, challenges, and future prospects. Key technologies such as IoT, UAVs, data analytics, and AI are highlighted for their contributions to optimizing crop yield, monitoring field variability, and improving farm management through data-driven decisions. The survey discusses applications in crop monitoring, irrigation, pest control, and autonomous systems, illustrating their transformative impact on farming. However, challenges such as high costs, data quality, technical expertise, and environmental constraints are identified as barriers to widespread adoption. The paper concludes by exploring future opportunities for enhancing system robustness, scalability, and socio-economic benefits, underscoring the potential of these technologies to foster sustainable agricultural practices. By addressing these challenges and leveraging emerging innovations, precision agriculture and smart farming can significantly contribute to global food security and environmental sustainability.

1 Introduction

1.1 Significance in Modern Agriculture

Precision agriculture and smart farming are essential in tackling the complex challenges of modern agriculture, including rising global food demand, resource scarcity, and environmental sustainability [1]. These practices utilize technologies such as machine learning (ML), the Internet of Things (IoT), and unmanned aerial vehicles (UAVs) to enhance agricultural productivity and sustainability. By integrating IoT and ML, precision agriculture significantly improves crop yield and quality, addressing the urgent need for efficient farming practices [2].

The deployment of smart farming technologies (SFT) plays a crucial role in boosting agricultural productivity, as they provide farmers with data-driven insights for informed decision-making [3]. These technologies enable real-time monitoring of crop health, soil conditions, and environmental factors, facilitating precise interventions that optimize resource use and minimize waste [4]. Furthermore, the effective implementation of smart farming, backed by supportive government policies and engagement from millennial farmers, is vital for achieving long-term agricultural sustainability [5].

In regions like Nigeria, where smallholder farmers struggle with low productivity and food insecurity, the integration of mobile technologies and precision agriculture tools presents a promising approach to enhance agricultural outcomes and improve food security [6]. Additionally, advancements in soil analysis technologies offer cost-effective and efficient methods for real-time soil health assessments, benefiting smallholder farmers and promoting sustainable practices [7].

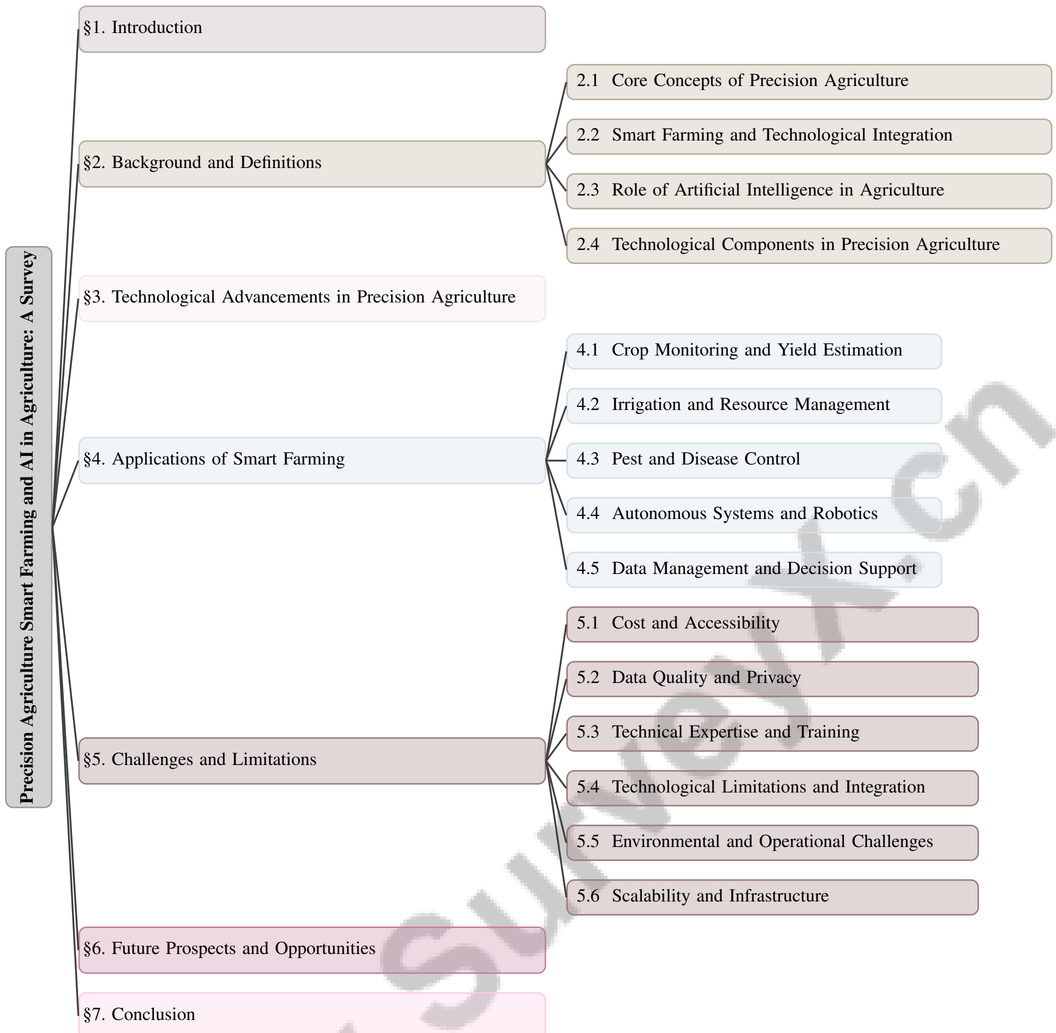

Figure 1: chapter structure

1.2 Structure of the Survey

This survey provides a comprehensive overview of the role and impact of precision agriculture, smart farming, and artificial intelligence (AI) in transforming modern agricultural practices. The paper is organized into several key sections, each addressing a specific aspect of these technologies.

The first section introduces fundamental concepts and emphasizes the significance of precision agriculture and smart farming in enhancing productivity and sustainability, establishing the critical role these technologies play in addressing contemporary agricultural challenges.

The second section presents background information and definitions, explaining core concepts such as precision agriculture, smart farming, and AI in agriculture, along with the technological components involved, including data analytics, GPS, IoT devices, and AI, which are integral to these advanced practices.

The third section examines recent technological advancements in precision agriculture, highlighting innovations in AI and machine learning, the role of IoT and sensor technologies, contributions of data analytics and big data, and the deployment of robotics and automation. It also discusses remote sensing and imaging technologies for monitoring crop health and yield.

The fourth section focuses on smart farming applications, showcasing successful implementations. It covers methods and technologies for crop monitoring and yield estimation, irrigation and resource

AI-generated, for reference only.

management, pest and disease control, autonomous systems and robotics, and data management and decision support systems.

The fifth section identifies challenges and limitations associated with precision agriculture and smart farming technologies, addressing issues such as cost and accessibility, data quality and privacy, the necessity for technical expertise and training, technological limitations and integration challenges, environmental and operational hurdles, and scalability and infrastructure concerns.

The sixth section explores future prospects and opportunities in precision agriculture and smart farming, discussing strategies to enhance system robustness and scalability, emerging technologies and innovations, and socio-economic and educational opportunities arising from advancements in these fields.

This paper synthesizes key themes, highlighting the transformative effects of precision agriculture, smart farming, and AI on contemporary agricultural practices. It underscores how these innovations leverage advanced technologies like IoT and big data analytics to enhance productivity, optimize resource use, and address critical challenges such as food security and environmental sustainability, particularly in light of a growing global population. Furthermore, it emphasizes the need for collaboration among stakeholders to fully realize the potential of these technological advancements in agriculture [8, 9].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Precision Agriculture

Precision agriculture enhances efficiency, sustainability, and productivity through advanced technologies. UAVs with multispectral sensors are pivotal for estimating chlorophyll content and optimizing resource application, addressing food scarcity and environmental sustainability challenges [2, 10]. Predictive capabilities for crop yields across fields inform decision-making [11]. UAVs also contribute to ecological restoration, such as grassland recovery, showcasing automation's role in combating ecological degradation [12].

In vineyards, computer vision techniques address challenges in detecting grape clusters under occlusion and varying light conditions [13]. Monitoring coffee fruit ripening, complicated by asynchronous flowering, highlights the need for advanced systems [4]. Precision agriculture leverages big data, cloud computing, and IoT for smart farming [1], aiding plant health monitoring through techniques like named entity recognition on social media data [14].

Applications include mobile chemical analysis systems for soil pH, offering cost-effective soil health assessments [7]. In regions like Nigeria, precision agriculture enhances productivity and addresses food insecurity [6]. As the global population is projected to reach 9 to 10 billion by 2050, precision agriculture is crucial for maximizing crop yields, minimizing waste, and ensuring economic viability while preserving natural resources through IoT, AI, and remote sensing integration [15, 8, 9, 16, 17].

2.2 Smart Farming and Technological Integration

Smart farming revolutionizes agricultural methodologies by integrating advanced technologies for efficiency and sustainability. IoT is central, enabling real-time data management for precise monitoring of parameters like soil moisture and temperature, optimizing irrigation and resource use [10]. The adoption of smart farming technologies (SFT) is shaped by social, organizational, and technological factors [3], encompassing IoT, machine learning, and blockchain to enhance decision-making and operational efficiency [5]. Machine learning predicts crop damage, while deep learning detects diseases, illustrating advanced computational applications in agriculture [2].

Computer vision technologies, such as the YOLOv7 algorithm, classify agricultural products like coffee fruits based on ripeness, enhancing decision-making [4]. Mixed reality interfaces augment this ecosystem, allowing remote monitoring and control of agricultural facilities by integrating real-world data into virtual environments [18]. Smart farming frameworks categorize technologies into domains like smart farming, livestock technology, and mobile solutions, crucial for enhancing productivity and market access [6]. This comprehensive approach highlights technological integration's role in optimizing agricultural practices and fostering resilience in global food systems.

2.3 Role of Artificial Intelligence in Agriculture

AI transforms agriculture by enhancing decision-making and operational efficiency, with applications in disease detection, crop management, and resource optimization. The YOLOv4 model enables early detection of plant diseases in tomatoes, while YOLOv8 integrated with RAG provides real-time disease identification, improving diagnostic accuracy [19, 20]. AI models like DGLR optimize resource management by capturing spatial and temporal correlations in soil moisture [21]. Machine learning predicts chlorophyll content in sugarcane, enhancing crop health monitoring [22], while AI predicts disease severity in sugar beet plants using UAV-captured multispectral images [23].

AI integrates diverse data sources for comprehensive analysis. Satellite imagery and weather data fusion improve downy mildew detection in vine crops, showcasing AI's capability to leverage diverse datasets [24]. CNNs enhance rice disease classification, addressing critical issues in sustainable production and food security [25]. Challenges in AI application include the absence of natural baselines and design difficulties due to changing distributions [26]. Low adoption rates of smart farming technologies in regions like Indonesia are compounded by an aging farmer population and high technology costs [5]. AI is pivotal for enhancing decision-making, optimizing resource management, and addressing crop health and productivity challenges, promoting sustainable and efficient farming practices [27].

2.4 Technological Components in Precision Agriculture

Precision agriculture employs technological components to enhance efficiency, sustainability, and productivity, including data analytics, GPS, IoT devices, and AI. Data analytics interprets large datasets for informed decision-making, while GPS supports precise field mapping and monitoring. IoT devices enable real-time data collection, improving resource management. AI analyzes data to predict outcomes and automate processes, enhancing productivity and sustainability [28, 8, 9].

Data analytics integrates and interprets extensive datasets; LTS-Net enhances localization by extracting stable features from point cloud data [29]. Adaptive path planning algorithms optimize UAV flight paths, improving monitoring precision [30]. GPS provides essential geolocation data for mapping and resource application, integrated with mobile systems and cloud computing for data management [7]. Models like MASHNET predict geographic coordinates from genomic data, illustrating deep learning's potential for geolocation predictions [31].

IoT devices facilitate precise monitoring of parameters like soil moisture and temperature, essential for effective interventions [1]. UAV-assisted sensor networks face data collection challenges due to UAV movements, highlighting the need for robust IoT frameworks [32]. AI, through machine learning and deep learning, enhances precision agriculture's analytical capabilities. Automating grapevine Leaf Area Index estimation using drone imagery exemplifies AI's integration into precision agriculture [33]. AI aids soil management by utilizing soil apparent electrical conductivity for water content management and yield prediction [34]. AI-driven methods like CHAPBILM integrate heuristic algorithms for UAV trajectory design, showcasing AI's potential in autonomous operations [12].

The integration of advanced technological components equips farmers with tools for effective data analysis, resource optimization, and enhanced crop management. This tech-driven approach addresses challenges posed by a growing global population and climate change, aiming to significantly increase agricultural productivity and sustainability while minimizing waste [8, 9].

3 Technological Advancements in Precision Agriculture

The agricultural sector's evolution hinges on integrating advanced technologies to boost productivity and sustainability. This section delves into the roles of artificial intelligence (AI) and machine learning (ML) innovations, examining their impacts on crop management, resource optimization, and decision-making processes. Table 5 provides a detailed classification of technological methods across different domains, illustrating their roles in advancing precision agriculture through enhanced data collection, analysis, and application. Table 1 presents a detailed classification of technological methods across different domains, illustrating their roles in advancing precision agriculture through enhanced data collection, analysis, and application. **??** illustrates the hierarchical structure of technological advancements in precision agriculture, highlighting five primary categories: AI and

AI-generated, for reference only.

Category	Feature	Method
AI and Machine Learning Innovations	Learning and Adaptation Interactive Visualization Efficient Geolocation	TL-RDC[25], MADRL-SA[32] MRD[18] MN[31]
IoT and Sensor Technologies	Collaborative Robotics Data Analysis Techniques Reinforcement Learning Constraints	ACM[35] ADM[36], AS[37] MADRL-AM[38]
Data Analytics and Big Data	Complex Data Analysis Real-Time Processing Scalability and Performance Economic Assessment	preLSTMMLP[39], DG2P[40], TSN[41] BDPCB[42] ADW[43], ADW[44] PAMCoBA[45]
Robotics and Automation	Optimization Techniques Integrated Systems Dynamic Adaptation	IDS[46], SSTRPVST[47], CCWG[48] IAPF[49], PAAN[50] MCDM[51]
Remote Sensing and Imaging Technologies	Comprehensive Mapping Image Fusion Techniques Robust Prediction Models Deep Learning Enhancements Dynamic Path Optimization	4DRM[52] OTFS[53] SVT[23] LAI-AE[33] APPA[30]

Table 1: This table provides a comprehensive overview of various technological methods categorized into five key areas: AI and Machine Learning Innovations, IoT and Sensor Technologies, Data Analytics and Big Data, Robotics and Automation, and Remote Sensing and Imaging Technologies. Each category lists specific features and the corresponding methods, supported by relevant citations, demonstrating their application in enhancing precision agriculture. The table highlights the diverse approaches employed to improve agricultural productivity and sustainability through technological advancements.

Machine Learning Innovations, IoT and Sensor Technologies, Data Analytics and Big Data, Robotics and Automation, and Remote Sensing and Imaging Technologies. Each category encompasses specific applications and techniques that enhance crop management, resource optimization, data collection, processing, predictive modeling, and monitoring capabilities, thereby contributing to increased agricultural productivity and sustainability.

3.1 AI and Machine Learning Innovations

AI and ML advancements have revolutionized precision agriculture by enhancing classification accuracy, resource management, and decision-making. Models such as LightGBM and Random Forest have proven effective in predicting crop damage and detecting diseases, underscoring ML's potential to improve agricultural outcomes [2]. Transfer learning with convolutional neural networks facilitates reliable rice disease classification, integrated into user-friendly applications for practical deployment [25].

For crop monitoring, models like Mask R-CNN, YOLOv2, and YOLOv3 effectively detect and segment grape clusters, tackling challenges such as occlusion and varying illumination [13]. Mixed reality interfaces, utilizing deformable neural radiance fields, create dynamic, real-time 3D environments for enhanced agricultural visualization [18].

UAV technology innovations, including the multi-UAV deep reinforcement learning-based scheduling algorithm, optimize operations by reducing packet loss and enhancing data collection through joint optimization of velocities and schedules [32]. The development of MASHNET offers an efficient, alignment-free approach to genomic geolocation, enabling precise agricultural applications even with noisy data [31].

As illustrated in Figure 2, these innovations in AI and machine learning within agriculture highlight key areas such as precision agriculture, crop monitoring, and UAV technology. Each area is supported by specific models and methods, demonstrating their application in enhancing agricultural productivity and efficiency. These AI and ML innovations collectively enhance accuracy, efficiency, and sustainability in farming practices, enabling precise analysis and decision-making that contribute to increased agricultural productivity [5].

3.2 IoT and Sensor Technologies

The integration of IoT and sensor technologies has transformed agricultural data collection and analysis, enhancing precision and efficiency. IoT devices enable real-time monitoring and data acquisition, optimizing operations by allowing precise control over parameters such as soil moisture,

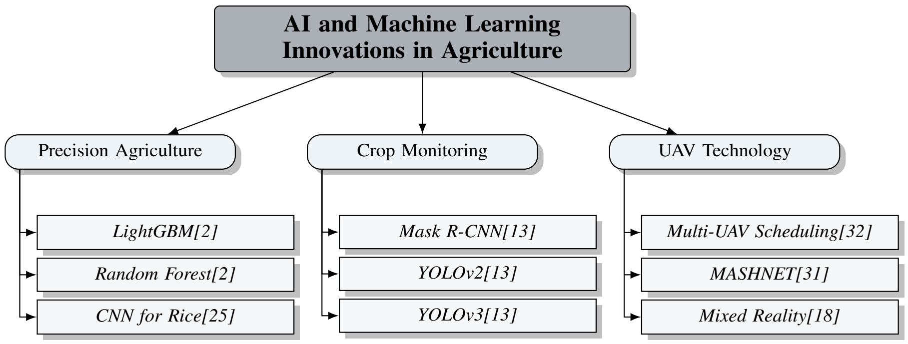

Figure 2: This figure illustrates the innovations in AI and machine learning within agriculture, highlighting key areas such as precision agriculture, crop monitoring, and UAV technology. Each area is supported by specific models and methods, demonstrating their application in enhancing agricultural productivity and efficiency.

temperature, and humidity [36]. This capability is crucial for efficient irrigation and resource utilization, contributing to sustainable agricultural outcomes [37].

Sensor networks, especially in UAV-assisted systems, have been optimized using multi-agent deep reinforcement learning frameworks, employing techniques like double deep Q-network with action masks to enhance task offloading in secure networks, ensuring robust data collection [38]. Unmanned ground vehicles equipped with sensors facilitate comprehensive data collection, demonstrating the effectiveness of collaborative UAV and UGV efforts in capturing detailed environmental and crop-specific data [35].

Sliding window analysis in sensor data processing allows for identifying and quantifying abnormalities in crop conditions, enhancing precision in monitoring and facilitating timely interventions [36]. IoT and sensor technologies are integral to modern precision agriculture, enabling data-driven decisions that significantly enhance crop yields and optimize resource utilization, addressing the projected 70

3.3 Data Analytics and Big Data

Method Name	Data Integration	Computational Techniques	Performance Metrics
preLSTMMLP[39]	Environmental Data Integration	Lstm Autoencoders	Economic Performance Metrics
BDPCB[42]	Lambda Architecture	Yolov5 Model	Mean Average Precision
ADW[43]	Etl Processes	Constellation Schema	Runtime Efficiency
ADW[44]	Effective Data Integration	Hive, Mongodb, Cassandra	Net Present Value
TSN[41]	-	Deep Learning Architecture	Mean Absolute Error
DG2P[40]	Genomic, Environmental,	Deep Learning Architecture	Net Present Value
PAMCoBA[45]	-	-	Net Present Value

Table 2: Summary of various data analytics and big data methodologies employed in agricultural research. The table highlights the integration of diverse data sources, computational techniques, and performance metrics used to enhance predictive accuracy and evaluate economic feasibility in precision agriculture.

Data analytics and big data are pivotal for enhancing agricultural outcomes through efficient processing, analysis, and interpretation of vast datasets. Integrating genomic and environmental data into predictive models, such as LSTM autoencoder-based deep neural networks, underscores data analytics' role in improving predictive accuracy [39]. This approach captures complex, non-linear interactions, leading to more accurate yield predictions and resource optimization.

High-throughput phenotyping pipelines, particularly in cotton, demonstrate big data's effectiveness in managing large volumes of data through cloud computing, facilitating real-time and batch processing [42]. The Agricultural Data Warehouse (ADW) plays a crucial role in managing and analyzing agricultural big data, enabling real-time analytics and improved decision-making [43]. The ADW's capacity to handle the volume, variety, velocity, and veracity of agricultural data ensures high performance and scalability, essential for modern agriculture's dynamic needs [44].

Advanced segmentation and localization techniques, such as the Triple-S Network, improve segmentation of complex agricultural imagery, enhancing precision in data analytics [41]. The use of deep learning models like DeepG2P highlights the importance of modeling complex interactions between genomic and environmental data for accurate crop yield predictions [40]. Evaluating precision agriculture technologies through economic performance metrics, such as the Net Present Value approach, illustrates data analytics' role in assessing technological investments' financial viability [45]. Table 2 provides a comprehensive overview of the data analytics and big data techniques utilized in agricultural studies, detailing the methods, data integration strategies, computational approaches, and performance metrics that facilitate improved decision-making and efficiency in agricultural practices.

3.4 Robotics and Automation

Method Name	Technological Integration	Environmental Impact	Operational Efficiency
IAPF[49]	Depth Camera	-	Improving Efficiency
PAAN[50]	Deep Reinforcement Learning	-	Collision-free Navigation
CCWG[48]	Deep Learning	-	Improve Waypoint Accuracy
IDS[46]	Heterogeneous Robot Teams	Enhanced Monitoring Accuracy	Increased Cost-effectiveness
MCDM[51]	Uav-BS Deployment	Minimize Interference	Optimize Uav-BS
SSTRPVST[47]	Not Mentioned	Not Mentioned	Improve Operational Efficiency

Table 3: Summary of various robotic and automation methods utilized in precision agriculture, detailing their technological integration, environmental impact, and operational efficiency. The table highlights the diverse applications of advanced technologies such as deep learning and UAV deployment in enhancing agricultural practices.

Robotics and automation are pivotal in advancing precision agriculture by enhancing efficiency, accuracy, and sustainability in farming operations. The integration of robotic systems into agricultural practices leverages advanced technologies like computer vision, machine learning, and drones to improve precision in tasks such as weed control and crop monitoring. Robotic spot spraying can reduce herbicide usage by up to 65

The Integrated Actuation-Perception Framework exemplifies advancements in robotic systems, allowing for precise identification, localization, and cutting of leaves from trees [49]. Position-agnostic autonomous systems utilizing deep reinforcement learning agents demonstrate robotics' potential in complex agricultural environments, processing depth images and robot state information to facilitate autonomous navigation [50]. Deep learning techniques like Contrastive Clustering for Waypoint Generation optimize the movement of autonomous vehicles in agricultural settings [48].

Robotic systems also aid in environmental monitoring and data collection, utilizing heterogeneous robot teams for efficient monitoring of spatiotemporal processes [46]. Multi-UAV systems adapt to dynamic environments while minimizing collisions and maximizing coverage, underscoring robotics' importance in precision agriculture [51]. The application of robotics in optimizing agricultural logistics, demonstrated by a three-phase matheuristic approach for sprayers and tankers, enhances operational efficiency [47].

Robotics and automation are revolutionizing precision agriculture by integrating technologies like IoT, AI, and ML, enhancing productivity, minimizing labor requirements, and fostering sustainable practices. This transformation is crucial in addressing the challenges posed by a projected global population of 9 to 10 billion by 2050, necessitating a 70

3.5 Remote Sensing and Imaging Technologies

Remote sensing and imaging technologies are pivotal in precision agriculture, providing advanced capabilities for monitoring crop health and yield. Table 4 provides a detailed overview of the remote sensing and imaging methods employed in precision agriculture, highlighting the technological platforms, analytical techniques, and their respective application domains. These technologies utilize various sensors and platforms, including UAVs and satellites, to capture high-resolution imagery that offers comprehensive insights into crop and field conditions. UAVs enable precise monitoring and analysis through sensors like RGB and spectral cameras, allowing for detailed assessments of vegetation classification, crop counting, yield predictions, and the detection of weeds, diseases, and nutrient deficiencies [54, 55].

Method Name	Technological Platforms	Analytical Techniques	Application Domains
APPA[30]	Uavs	Deep Learning	Crop Health Monitoring
OTFS[53]	Jilin-1 Dataset	Instance Segmentation	Cultivated Land Segmentation
LAI-AE[33]	Drone Imagery	Deep Learning	Precision Agriculture
4DRM[52]	Ground Vehicle	4D Reconstruction	Crop Monitoring
SVT[23]	Uav Imagery	Deep Learning	Disease Severity

Table 4: Overview of various remote sensing and imaging methods utilized in precision agriculture, detailing the technological platforms, analytical techniques, and application domains. This table highlights the diversity of approaches, from UAV-based deep learning methods for crop health monitoring to 4D reconstruction techniques for comprehensive crop monitoring.

UAVs present a superior alternative to traditional satellite imagery due to their ability to collect high-resolution data cost-effectively and flexibly [16]. Advanced sensors on UAVs capture detailed multispectral images essential for granular crop health monitoring, while adaptive path planning enhances mapping efficiency based on observed information content [30].

Image segmentation frameworks are crucial for utilizing remote sensing techniques to monitor fruit health and yield. The overlap-tile fusion strategy merges predictions from overlapping image tiles, achieving continuous segmentation results in remote sensing images, which is instrumental in detecting anomalies [53]. Integrating deep learning techniques with traditional feature extraction methods improves the accuracy of Leaf Area Index estimation from drone imagery, demonstrating the potential applications of these technologies in precision agriculture [33].

Advanced methods like the 4D Reconstruction Method leverage multi-sensor SLAM pipelines to achieve comprehensive 4D reconstructions of agricultural fields, enhancing the understanding of spatial and temporal dynamics [52]. Models like SugarViT effectively model uncertainty in label distribution, allowing robust predictions despite variability in plant disease expression [23]. Harmonizing crop type datasets significantly enhances foundation models' ability to generalize across regions, underscoring the need for larger, balanced datasets in agricultural remote sensing [56].

Remote sensing and imaging technologies are essential for modern precision agriculture, enabling comprehensive crop monitoring and management to meet increasing food demands while minimizing environmental impacts. These technologies facilitate various applications, including irrigation management, nutrient application, disease and pest control, and yield prediction. Recent advancements in machine learning and deep learning techniques have further enhanced the ability to analyze and segment crops effectively, allowing for informed decision-making and optimized agricultural practices [57, 16]. By leveraging these technologies, farmers can optimize resource use, improve crop health, and increase yield, ultimately contributing to sustainable agricultural practices.

Feature	AI and Machine Learning Innovations	IoT and Sensor Technologies	Data Analytics and Big Data
Data Collection Method	Predictive Models	Real-time Sensors	Large Datasets
Technological Integration	Neural Networks	Iot Devices	Cloud Computing
Application Focus	Crop Monitoring	Resource Optimization	Predictive Modeling

Table 5: This table provides a comparative analysis of three technological domains integral to precision agriculture: AI and machine learning innovations, IoT and sensor technologies, and data analytics and big data. It highlights the distinct data collection methods, technological integrations, and application focuses associated with each domain, underscoring their roles in advancing agricultural productivity and sustainability.

4 Applications of Smart Farming

The applications of smart farming are pivotal in addressing contemporary agricultural challenges, focusing on enhancing productivity and sustainability. This section delves into crop monitoring and yield estimation, irrigation and resource management, pest and disease control, autonomous systems and robotics, and data management and decision support.

4.1 Crop Monitoring and Yield Estimation

Crop monitoring and yield estimation leverage advanced technologies to improve agricultural outcomes. IoT devices automate processes, optimizing resource use and enhancing crop yields [10]. UAVs equipped with multispectral cameras provide high-resolution imagery for detailed 3D mapping, enabling comprehensive spatial analysis [58]. These technologies detect early stress signs, such as drought, using aerial imagery and deep learning [59]. Deep neural networks, like MASHNET, predict geographic origins and can be adapted for yield estimation by capturing spatial correlations [31].

Mobile applications such as 'CoffeApp' utilize computer vision to analyze fruit ripening stages, offering real-time insights and personalized disease management recommendations [4, 25]. Real-time semantic segmentation techniques enable precise crop and weed differentiation, facilitating precision agriculture [60]. Machine learning advancements allow rapid, non-destructive chlorophyll content assessments, crucial for monitoring crop health and yield estimation [22]. Mobile robots provide continuous soil apparent electrical conductivity (ECa) measurements, enhancing accuracy and efficiency [34].

As illustrated in Figure 3, the hierarchical structure of crop monitoring and yield estimation underscores the integral role of these advanced technologies, applications, and robotics in optimizing agricultural productivity. These innovations optimize resource use, ensuring higher productivity and resilience against environmental challenges.

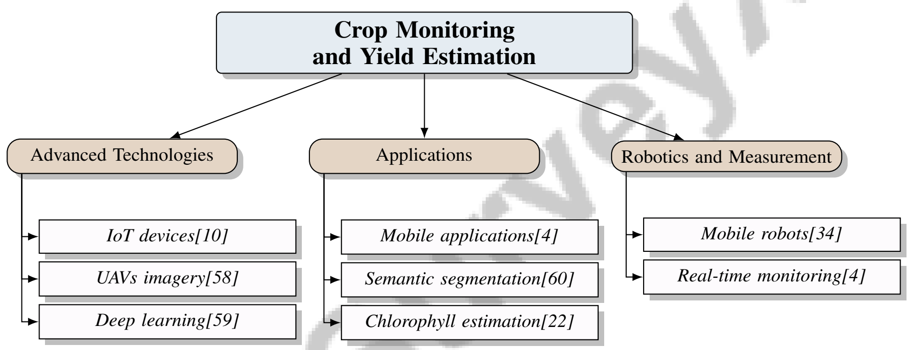

Figure 3: This figure illustrates the hierarchical structure of crop monitoring and yield estimation, highlighting the role of advanced technologies, applications, and robotics in optimizing agricultural productivity.

4.2 Irrigation and Resource Management

Efficient irrigation and resource management are central to smart farming, focusing on optimizing water use and enhancing productivity. Sensor-based smart irrigation systems adjust water usage based on real-time data, improving sustainability [61]. These systems monitor soil moisture levels, ensuring optimal water delivery, crucial for crop yield quality and quantity [62]. Proximal Gamma Ray Spectroscopy aids effective water management by monitoring soil water content, enabling informed irrigation decisions [63]. IoT applications enhance irrigation efficiency through modular approaches and real-time data acquisition [64].

Matheuristic approaches optimize routes for sprayers and tankers, minimizing resource wastage and enhancing irrigation precision [47]. These technologies achieve sustainable irrigation and resource management, contributing to increased agricultural productivity and resilience.

4.3 Pest and Disease Control

Advanced technologies in pest and disease control optimize agricultural productivity. Deep learning models like YOLOv8 improve disease detection accuracy and efficiency [65]. The I-YOLOv4 model demonstrates high precision in detecting tomato plant diseases, showcasing object detection algorithms' effectiveness [19]. Low-power devices for real-time pest detection offer cost-effective alternatives, such as smart trap systems using machine learning to analyze pheromone trap images [66]. This integration reduces costs and environmental impact, supporting sustainable practices [67].

Systems like the Intelligent Scarecrow Monitoring System enhance crop protection through real-time detection [68]. ChatGPT integration in agricultural data management improves stakeholder accessibility, promoting effective pest management strategies [69]. Synthetic datasets enhance model performance in distinguishing crops from weeds, crucial for pest and disease management [70]. Advanced methods, such as integrating RAG with real-time detection systems, offer improved accuracy and adaptability [20]. Modeling prediction uncertainty, as shown by SugarViT, enhances accuracy by integrating environmental data [23]. Integrating heterogeneous data sources effectively detects downy mildew in vine crops with remarkable accuracy [24].

Smart farming technologies in pest and disease control provide innovative solutions that enhance precision, reduce environmental impact, and promote sustainability. Technologies such as IoT, AI, and big data analytics revolutionize smart farming, enabling effective management strategies crucial for increasing productivity and resilience amid challenges like climate change and a growing global population projected to reach 9 billion by 2050 [61, 8, 9].

4.4 Autonomous Systems and Robotics

Autonomous systems and robotics transform farm operations by enhancing efficiency, reducing labor demands, and increasing precision. The integration of robotics in precision agriculture, exemplified by the Integrated Actuation-Perception Framework, automates leaf sampling, improving accuracy and efficiency [49]. Vision-assisted systems for autonomous harvesting, like the bimanual system for avocados, stabilize the peduncle and autonomously detach fruit, showcasing robotic capabilities [71]. Visual servoing-based navigation systems provide cost-effective solutions, enhancing adaptability [72].

Deep semantic segmentation algorithms in motion controllers enable autonomous navigation with low-cost equipment, enhancing operations in complex environments [73]. Methodologies for digital map reconstruction and VR remote operation control improve operator immersion and efficiency [74]. Advanced waypoint prediction methods significantly enhance navigation accuracy in complex crop layouts [48]. These innovations contribute to transforming agricultural practices, promoting sustainability and resilience.

4.5 Data Management and Decision Support

Data management systems are crucial for supporting decision-making in smart farming by organizing, analyzing, and visualizing agricultural data. Methods like counterfactual analysis using neural networks enhance precision agriculture decision-making by categorizing field points into management zones based on fertilizer responsiveness [75]. These systems optimize resource allocation and improve farm productivity.

Selective privacy models in IoT-enabled smart farms facilitate less stringent security measures on non-sensitive data, optimizing energy use and ensuring efficient data processing for real-time decision-making [76]. Effective task offloading management in high-density IoT environments enhances operational efficiency and sustainability [38]. Anomaly detection techniques, such as Autoencoder models, ensure sensor data reliability, supporting accurate decision-making [77]. Monitoring systems that maximize information gain increase cost-effectiveness and accuracy [46].

Platforms like Pignoletto provide unified data management solutions, enhancing decision-making through visualization and analysis of heterogeneous data sources [78]. Mobile platforms such as 'Sell Harvest' connect farmers with buyers, offering features crucial for informed decision-making and market engagement [6]. Mixed reality interfaces enhance data management by allowing users to engage with digital twins through immersive visualizations, supporting decision-making in smart farming [18]. Data management systems optimize decision-making, providing tools for efficient resource management, enhanced productivity, and sustainable agricultural practices.

5 Challenges and Limitations

Precision agriculture faces several challenges that hinder the effective adoption of advanced technologies, including financial constraints, accessibility issues, and the necessity for technical expertise.

AI-generated, for reference only.

Addressing these barriers is essential for developing strategies that promote innovative practices in agriculture.

5.1 Cost and Accessibility

The adoption of advanced technologies in precision agriculture is significantly hindered by financial and accessibility barriers. High initial costs for equipment such as sensors, UAVs, and IoT devices pose substantial burdens, especially in resource-limited settings [5]. Compiling extensive annotated datasets for training CNNs is both costly and time-consuming [25]. Accessibility issues stem from a lack of education and awareness among farmers and a reluctance to abandon traditional practices [5]. Dependence on high-quality camera setups, which may not be feasible for all users, further restricts technology adoption [18]. Moreover, genomic geolocation methods require significant computational resources, limiting their application in non-model organisms [31].

Figure 4 illustrates the primary barriers to adopting precision agriculture technologies, categorized into financial, accessibility, and technical challenges. This figure highlights key issues such as equipment costs, lack of education, and computational resource demands, which collectively impede the integration of innovative agricultural practices.

To address these challenges, algorithms that minimize computational and communication complexity are needed, making them suitable for large-scale agricultural settings. Innovative methods that utilize minimal labeled data and adapt to diverse environments without extensive hardware investments show promise in overcoming financial and accessibility hurdles. Leveraging advancements in IoT and AI is crucial for enhancing productivity and sustainability amid growing global demands and climate variability. Collaborative efforts among stakeholders can optimize agricultural practices and improve decision-making through efficient data management [8, 79]. Overcoming these barriers can enhance technology adoption, leading to greater efficiency and sustainability in the agricultural sector.

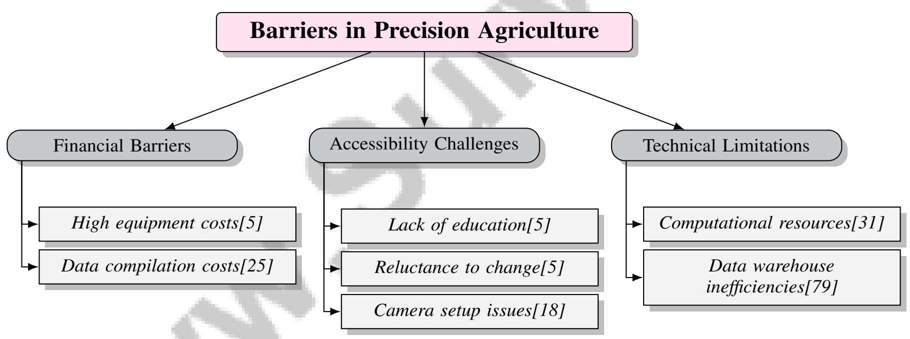

Figure 4: This figure illustrates the primary barriers to adopting precision agriculture technologies, categorized into financial, accessibility, and technical challenges, highlighting key issues such as equipment costs, lack of education, and computational resource demands.

5.2 Data Quality and Privacy

Data quality and privacy are pivotal concerns in smart farming, affecting the effectiveness and acceptance of precision agriculture practices. Variability in environmental conditions can introduce noise and inaccuracies into data models, complicating predictive capabilities. For example, reliance on generated images that do not accurately represent ground truth can degrade model performance [24]. Toy datasets that fail to capture real-world complexities exacerbate data quality issues, limiting research applicability [1]. A significant obstacle in training models for tasks like Named Entity Recognition (NER) and Named Entity Linking (NEL) on social media platforms is the scarcity of labeled data, leading to ambiguity and noise that challenge reliable plant health monitoring [14]. The dynamic nature of UAV movements can also result in poor channel conditions and packet loss, complicating data collection efforts [32].

Privacy and security concerns are critical, particularly given the vulnerabilities of IoT devices to manipulation and breaches. Wireless communication networks are susceptible to malicious activities, threatening the integrity of smart farming operations. Implementing robust data management practices

AI-generated, for reference only.

is essential to address these vulnerabilities, which can significantly impact crop productivity and system integrity. By leveraging IoT and big data analytics, stakeholders can enhance the protection of sensitive agricultural data, ensuring effective decision-making and resource optimization while mitigating cyber threats [80, 8, 79, 9].

Developing advanced data management strategies that enhance data quality, security, and reliability is imperative. Improving data quality and implementing robust privacy measures can significantly enhance operational efficiency, foster trust among stakeholders, and facilitate broader adoption within agriculture. This transformation is crucial as precision agriculture employs technologies like IoT, machine learning, and big data analytics to optimize crop yields, reduce waste, and address food security and environmental sustainability challenges amid a growing global population [8, 9, 61, 69, 79].

5.3 Technical Expertise and Training

Implementing smart farming solutions requires significant technical expertise and training, posing challenges for agricultural stakeholders. The complexity of technologies such as computer vision and deep learning necessitates a thorough understanding of algorithms and the ability to manage large datasets. This complexity is particularly evident in tasks like weed detection, where the small size and variability of weeds can hinder classification accuracy [81]. The reliance on extensive datasets and environmental variability further complicates the deployment of high-throughput systems, emphasizing the need for specialized knowledge [82].

Collecting and annotating large-scale datasets across various growth stages and environmental conditions is labor-intensive and time-consuming, underscoring the importance of training programs to equip farmers and agricultural professionals with necessary skills [83]. The survey highlights the need for organizational support in implementing smart farming technologies, as technical expertise alone may not suffice [3].

Platforms like Pignoletto aim to mitigate these challenges by providing user-friendly interfaces and reducing the technical barriers for farmers, facilitating the adoption of smart farming technologies [78]. By offering accessible tools and resources, these platforms bridge the gap between technological advancements and practical agricultural applications, enabling farmers to leverage innovations to enhance productivity and sustainability.

5.4 Technological Limitations and Integration

Integrating advanced technologies in precision agriculture is challenged by technological limitations and system interoperability complexities. A significant issue is the scalability and reliability of local sensor data, affecting distributed data processing in IoT-enabled systems [84]. The scalability challenge is compounded by benchmarks that present difficulties for algorithms not designed to handle larger problem sizes [85].

The deployment of robot teams for effective monitoring must balance cost with the intermittent nature of agricultural tasks, as existing methods often overlook this aspect [46]. In large wireless sensor networks, the complex connectivity graph can require global information for accurate localization, posing challenges for existing algorithms [86]. Technical complexities and regulatory hurdles associated with UAVs hinder their widespread adoption [87]. UAVs also face limitations such as restricted battery life and load capacity, impeding their ability to perform extensive tasks like restoring multiple degraded areas in a single flight [12].

Integration challenges are further complicated by performance variability across different crop types and environmental conditions, necessitating adaptable solutions [48]. Adaptive path planning methods may struggle in heterogeneous field structures, affecting decision-making accuracy [30]. Existing SLAM methods often do not suit agricultural environments due to their reliance on stable features, which can change seasonally [29]. Synchronization complexities in vehicle routing can lead to increased computational times, particularly for larger instances, posing challenges for efficient resource management [47]. The low technology adoption rate among older farmers and insufficient educational resources further limit the integration of new technologies in farming practices [5].

Addressing these technological limitations and integration challenges is crucial for advancing precision agriculture and maximizing the benefits of smart farming technologies. Effectively tackling the challenges posed by climate change, resource scarcity, and the need for increased food production to support a projected global population of 9 to 10 billion by 2050 can significantly enhance efficiency, sustainability, and resilience in agriculture. Advanced technologies such as IoT, AI, and precision agriculture methods will enable farmers to optimize resource management, enhance crop yields, and reduce environmental impacts, transforming traditional farming into a more data-driven and innovative approach [88, 55, 8, 9].

5.5 Environmental and Operational Challenges

Implementing precision agriculture encounters environmental and operational challenges that can significantly impact effectiveness and efficiency. A primary concern is the dependency of certain technologies on environmental conditions, which can limit operational capabilities. For instance, LoRa-based cattle monitoring systems relying on solar energy may struggle during prolonged low sunlight periods, affecting data transmission and reliability [89]. Similarly, UAV-based avocado harvesting methods face limitations due to UAV payload capacity and the complexities of operating in intricate agricultural environments [71].

Extreme environmental conditions pose additional challenges for autonomous navigation systems, where depth perception impairments can affect motion planning accuracy and reliability [90]. The Pheno-Robot, designed for in-situ digital modeling, encounters difficulties in complex terrains and varying conditions, highlighting robotic limitations in precision agriculture [91]. Terrain variability presents a substantial challenge, as precision agriculture technologies must adapt to diverse landscapes. Effectiveness can be compromised in highly variable conditions or when sensor data is influenced by environmental factors, leading to inaccuracies in data interpretation and decision-making [92]. Developing robust systems capable of adapting to dynamic conditions while maintaining efficiency is critical.

Addressing environmental and operational challenges is essential for the successful implementation of precision agriculture, which leverages advanced technologies and data analytics to enhance productivity while minimizing environmental impacts. This approach is vital in light of projected population growth, necessitating significant increases in global food production by 2050. Optimizing resource use and adapting to the spatial and temporal variabilities of agricultural fields is imperative [93, 9]. Developing technologies resilient to environmental fluctuations and operational complexities will enhance the sustainability and productivity of farming practices, contributing to more resilient agricultural systems.

5.6 Scalability and Infrastructure

Scaling smart farming solutions presents significant challenges due to the complexity of integrating advanced technologies with existing agricultural infrastructure. A key issue is the scalability of data processing systems, which must manage vast amounts of data generated by IoT devices and sensors in real-time [84]. The deployment of IoT-enabled systems often requires robust infrastructure to support distributed data processing, ensuring efficient data collection, transmission, and analysis across large agricultural operations.

Infrastructure limitations, such as inadequate connectivity and power supply, complicate the scalability of smart farming technologies. For example, reliance on solar-powered systems can be problematic in regions with limited sunlight, affecting the reliability of IoT devices and wireless sensor networks [89]. Regulatory hurdles and technical limitations, such as restricted UAV flight times and payload capacities, further constrain scalability for extensive farming applications [87]. The complexity of vehicle routing and synchronization in agricultural logistics also presents scalability challenges. Efficient resource management requires sophisticated algorithms capable of optimizing routes and schedules in dynamic environments; however, the computational demands of these algorithms can rise significantly with larger problem instances, leading to scalability issues [47]. Furthermore, the variability in environmental conditions across different landscapes necessitates adaptable solutions that maintain performance despite changes in terrain and climate [92].

To address these challenges, developing scalable infrastructure that supports the integration of advanced technologies into existing agricultural systems is essential. Key components include enhancing connectivity through advanced communication networks, particularly utilizing Ambient IoT (A-IoT) technologies for low-cost, battery-free operation; improving power supply solutions to

AI-generated, for reference only.

ensure uninterrupted IoT device functioning; and developing scalable data processing frameworks that efficiently manage large data volumes through hierarchical aggregation and fog computing, alleviating communication bottlenecks and optimizing energy use for real-time monitoring and decision-making in agricultural environments [28, 94, 84]. Overcoming these infrastructure-related obstacles will enable the agricultural sector to fully realize the potential of smart farming technologies, leading to increased productivity, sustainability, and resilience in farming practices.

6 Future Prospects and Opportunities

6.1 Enhancing System Robustness and Scalability

The future of agriculture hinges on robust and scalable smart farming systems to ensure sustainable productivity. Key research areas include integrating advanced architectures for improved segmentation and droplet identification, essential for system robustness [95]. Adapting systems like CHMS to various fruit types through refined pseudo-labeling and unsupervised techniques is crucial for scalability [96]. Innovations such as volumetric-based sensors can enhance trash level quantification, while improving energy efficiency in pest detection systems is vital for model robustness. Incorporating waypoint generators into navigation pipelines can further bolster system resilience [48].

Reducing computational complexity and validating strategies through real-world experiments are essential steps [46]. Enhancing LTS-Net with comprehensive seasonal data can improve feature extraction and localization [29]. Additionally, refining segmentation granularity for nitrogen-responsive regions will boost yield forecast confidence [11]. Optimizing UAV energy consumption and refining software architecture for robustness are necessary for long-duration operations. Future research should focus on evaluations to enhance decision-making and data quality [84]. These strategies aim to enhance the robustness and scalability of smart farming systems, fostering resilient agricultural practices.

6.2 Emerging Technologies and Innovations

Emerging technologies promise to revolutionize agriculture by enhancing precision, efficiency, and sustainability. Research should focus on predictive models using oversampling, hyperparameter optimization, and IoT implementations across diverse settings [2]. Multi-UAV systems for grassland restoration, incorporating 3D terrain considerations, are expected to enhance ecological restoration [12]. Expanding datasets, particularly for grape detection, and integrating additional sensing modalities can improve model robustness [13]. Optimizing models for mobile platforms is crucial for CNN applicability in agriculture [25].

In mixed reality, enhancing real-time streaming and refining interfaces are vital for commercial adaptation, improving user experience and efficiency [18]. Advanced machine learning techniques can significantly improve UAV system performance in diverse scenarios [32]. Leveraging technologies like IoT, AI, and mobile applications can enhance resilience and productivity, addressing the challenges of a projected global population of 9 billion by 2050, requiring a 70

6.3 Socio-Economic and Educational Opportunities

Smart farming advancements offer significant socio-economic and educational opportunities, transforming agricultural practices and rural communities. IoT and data-driven technologies enable large-scale smart farming implementation, enhancing productivity and resource management. Developing cost-effective IoT solutions and improving farmer education are crucial for widespread adoption [5]. Integrating adaptive information systems and robust infrastructure is essential for optimizing productivity and sustainability amid climate change, population growth, and resource scarcity. Advanced technologies like IoT and AI can transform traditional practices, enhance monitoring, and improve efficiency, addressing the need for a 70

Advancing user-friendly technologies that align with farmers' knowledge and address ethical data governance is essential for empowering farmers and fostering active participation in smart farming. This is crucial as agriculture faces the dual challenges of increasing food production to meet the demands of a projected global population of 9 to 10 billion by 2050 while mitigating traditional farming's environmental impacts. Integrating IoT, AI, and precision agriculture tools can enhance productivity and sustainability, requiring collaborative efforts to ensure accessibility and ethical data management [28, 5, 8, 9]. Exploring smartphone-based methods across crops and their integration with precision agriculture technologies presents opportunities for expanding smart farming solutions' accessibility and applicability.

Future research should focus on optimizing frameworks for constrained environments, enhancing image and audio processing, and exploring large language models (LLMs) in agricultural data analytics. These efforts can provide valuable socio-economic and educational opportunities, enabling efficient data communication infrastructures and integrating machine and sensor data in agricultural analysis. These advancements can contribute to sustainable agricultural development and improved livelihoods for farming communities [5].

7 Conclusion

The integration of IoT and AI technologies is revolutionizing modern agriculture by significantly improving productivity, sustainability, and resource management. These technologies enable precision agriculture through meticulous data collection and analysis, which are essential for refining farming practices. The use of fixed exposure settings in multispectral imaging enhances radiometric precision, thereby boosting the reliability of precision agriculture methodologies.

The collaboration between data scientists and farmers is essential for crafting effective smart farming solutions that boost efficiency while respecting traditional agricultural practices. The availability of high-quality labeled data is crucial for enhancing model accuracy in identifying productive crop fields, which is a cornerstone for advancing precision agriculture. Moreover, observational causal inference frameworks equip farmers with evidence-based decision support, fostering informed and sustainable agricultural practices.

Innovative deep learning techniques for assessing post-spraying effectiveness have achieved precise classification and quantification of spray deposits, highlighting the potential of advanced technologies in precision agriculture. Comprehensive experiments have validated sophisticated methods for waypoint generation in row-based crops, underscoring their transformative impact on agricultural practices. Additionally, the use of maps from previous sessions in agricultural environments demonstrates the feasibility of long-term application, despite environmental variability.

Precision agriculture, smart farming, and AI are thus instrumental in transforming modern agriculture by enhancing decision-making, optimizing resource utilization, and fostering sustainable practices, setting the stage for a more resilient and efficient agricultural future.

AI-generated, for reference only.

References

[1] Bikram Pratim Bhuyan, Ravi Tomar, Maanak Gupta, and Amar Ramdane-Cherif. An ontological knowledge representation for smart agriculture, 2021.

[2] Satvik Garg, Pradyumn Pundir, Himanshu Jindal, Hemraj Saini, and Somya Garg. Towards a multimodal system for precision agriculture using iot and machine learning, 2021.

[3] Carlo Giua, Valentina Cristiana Materia, and Luca Camanzi. Smart farming technologies adoption: Which factors play a role in the digital transition? *Technology in Society*, 68:101869, 2022.

[4] Francisco Eron, Muhammad Noman, Raphael Ricon de Oliveira, Deigo de Souza Marques, Rafael Serapilha Durelli, Andre Pimenta Freire, and Antonio Chalfun Junior. Computer vision-aided intelligent monitoring of coffee: Towards sustainable coffee production, 2023.

[5] Rika Reviza Rachmawati. Smart farming 4.0 untuk mewujudkan pertanian indonesia maju, mandiri, dan modern. In *Forum Penelitian Agro Ekonomi*, volume 38, pages 137–154, 2020.

[6] Mudathir Muhammad Salahudeen, Muhammad Auwal Mukhtar, Saadu Salihu Abubakar, and Salawu I. S. Mobile technology: A panacea to food insecurity in nigeria – a case study of sell harvest application, 2024.

[7] Ademir Ferreira da Silva, Ricardo Luis Ohta, Jaione Tirapu Azpiroz, Matheus Esteves Fereira, Daniel Vitor Marçal, André Botelho, Tulio Coppola, Allysson Flavio Melo de Oliveira, Murilo Bettarello, Lauren Schneider, Rodrigo Vilaça, Noorunisha Abdool, Vanderlei Junior, Wellington Furlaneti, Pedro Augusto Malanga, and Mathias Steiner. Artificial intelligence enables mobile soil analysis for sustainable agriculture, 2022.

[8] Emmanuel Kojo Gyamfi, Zag ElSayed, Jess Kropczynski, Mustapha Awinsongya Yakubu, and Nelly Elsayed. Agricultural 4.0 leveraging on technological solutions: Study for smart farming sector, 2024.

[9] EMBM Karunathilake, Anh Tuan Le, Seong Heo, Yong Suk Chung, and Sheikh Mansoor. The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture*, 13(8):1593, 2023.

[10] Dewan Md Nur Anjum Ashir, Md. Taimur Ahad, Manosh Talukder, and Tahsinur Rahman. Internet of things (iot) based smart agriculture aiming to achieve sustainable goals, 2022.

[11] Giorgio Morales and John W. Sheppard. Two-dimensional deep regression for early yield prediction of winter wheat, 2021.

[12] Dongbin Jiao, Lingyu Wang, Peng Yang, Weibo Yang, Yu Peng, Zhanhuan Shang, and Fengyuan Ren. Energy-sensitive trajectory design and restoration areas allocation for uav-enabled grassland restoration, 2022.

[13] Thiago T. Santos, Leonardo L. de Souza, Andreza A. dos Santos, and Sandra Avila. Grape detection, segmentation and tracking using deep neural networks and three-dimensional association, 2020.

[14] Shufan Jiang, Rafael Angarita, Stéphane Cormier, and Francis Rousseaux. Named entity recognition for monitoring plant health threats in tweets: a choubert approach, 2023.

[15] Adil Z. Babar and Ozgur B. Akan. Sustainable and precision agriculture with the internet of everything (ioe), 2025.

[16] Rajendra P Sishodia, Ram L Ray, and Sudhir K Singh. Applications of remote sensing in precision agriculture: A review. *Remote sensing*, 12(19):3136, 2020.

[17] Athanasios Balafoutis, Bert Beck, Spyros Fountas, Jurgen Vangeyte, Tamme Van der Wal, Iria Soto, Manuel Gómez-Barbero, Andrew Barnes, and Vera Eory. Precision agriculture technologies positively contributing to ghg emissions mitigation, farm productivity and economics. *Sustainability*, 9(8):1339, 2017.

[18] Byunghyun Ban. Mixed reality interface for digital twin of plant factory, 2022.

[19] Arunabha M. Roy, Rikhi Bose, and Jayabrata Bhaduri. A fast accurate fine-grain object detection model based on yolov4 deep neural network, 2021.

[20] Selva Kumar S, Afifah Khan Mohammed Ajmal Khan, Imadh Ajaz Banday, Manikantha Gada, and Vibha Venkatesh Shanbhag. Overcoming llm challenges using rag-driven precision in coffee leaf disease remediation, 2024.

[21] Anoushka Vyas and Sambaran Bandyopadhyay. Dynamic structure learning through graph neural network for forecasting soil moisture in precision agriculture, 2022.

[22] Amarasingam Narmilan, Felipe Gonzalez, Arachchige Surantha Ashan Salgadoe, Unupen Widanelage Lahiru Madhushanka Kumarasiri, Hettiarachchige Asiri Sampageeth Weerasinghe, and Buddhika Rasanjana Kulasekara. Predicting canopy chlorophyll content in sugarcane crops using machine learning algorithms and spectral vegetation indices derived from uav multispectral imagery. *Remote Sensing*, 14(5):1140, 2022.

[23] Maurice Günder, Facundo Ramón Ispizua Yamati, Abel Andree Barreto Alcántara, Anne-Katrin Mahlein, Rafet Sifa, and Christian Bauckhage. Sugarvit – multi-objective regression of uav images with vision transformers and deep label distribution learning demonstrated on disease severity prediction in sugar beet, 2024.

[24] William Maillet, Maryam Ouhami, and Adel Hafiane. Fusion of satellite images and weather data with transformer networks for downy mildew disease detection, 2022.

[25] Biplov Paneru, Bishwash Paneru, and Krishna Bikram Shah. Analysis of convolutional neural network-based image classifications: A multi-featured application for rice leaf disease prediction and recommendations for farmers, 2024.

[26] Michal Töpfer, František Plášil, Tomáš Bureš, Petr Hnětynka, Martin Kruliš, and Danny Weyns. Online ml self-adaptation in face of traps, 2023.

[27] Aashu, Kanchan Rajwar, Millie Pant, and Kusum Deep. Application of machine learning in agriculture: Recent trends and future research avenues, 2024.

[28] Eissa Alreshidi. Smart sustainable agriculture (ssa) solution underpinned by internet of things (iot) and artificial intelligence (ai). *arXiv preprint arXiv:1906.03106*, 2019.

[29] Riccardo Polvara, Sergi Molina Mellado, Ibrahim Hroob, Grzegorz Cielniak, and Marc Hanheide. Collection and evaluation of a long-term 4d agri-robotic dataset, 2022.

[30] Felix Stache, Jonas Westheider, Federico Magistri, Marija Popović, and Cyrill Stachniss. Adaptive path planning for uav-based multi-resolution semantic segmentation, 2021.

[31] Cai W. John, Owen Queen, Wellington Muchero, and Scott J. Emrich. Deep learning for reference-free geolocation for poplar trees, 2023.

[32] Yousef Emami. Deep reinforcement learning for joint cruise control and intelligent data acquisition in uavs-assisted sensor networks, 2023.

[33] Muhammad Waseem Akram, Marco Vannucci, Giorgio Buttazzo, Valentina Colla, Stefano Roccella, Andrea Vannini, Giovanni Caruso, Simone Nesi, Alessandra Francini, and Luca Sebastiani. Automating grapevine lai features estimation with uav imagery and machine learning, 2024.

[34] Dimitrios Chatziparaschis, Elia Scudiero, and Konstantinos Karydis. Robot-assisted soil apparent electrical conductivity measurements in orchards, 2023.

[35] Ciro Potena, Raghav Khanna, Juan Nieto, Roland Siegwart, Daniele Nardi, and Alberto Pretto. Agricolmap: Aerial-ground collaborative 3d mapping for precision farming, 2019.

[36] Aminul Huq, Dimitris Zermas, and George Bebis. Identification of abnormality in maize plants from uav images using deep learning approaches, 2023.

[37] Leonardo Saraceni, Ionut M. Motoi, Daniele Nardi, and Thomas A. Ciarfuglia. Agrisort: A simple online real-time tracking-by-detection framework for robotics in precision agriculture, 2023.

[38] Tingnan Bao, Aisha Syed, William Sean Kennedy, and Melike Erol-Kantarci. Sustainable task offloading in secure uav-assisted smart farm networks: A multi-agent drl with action mask approach, 2024.

[39] Guanjin Wang, Junyu Xuan, Penghao Wang, Chengdao Li, and Jie Lu. Lstm autoencoder-based deep neural networks for barley genotype-to-phenotype prediction, 2024.

[40] Swati Sharma, Aditi Partap, Maria Angels de Luis Balaguer, Sara Malvar, and Ranveer Chandra. Deepg2p: Fusing multi-modal data to improve crop production, 2022.

[41] Peri Akiva, Kristin Dana, Peter Oudemans, and Michael Mars. Finding berries: Segmentation and counting of cranberries using point supervision and shape priors, 2020.

[42] Amanda Issac, Alireza Ebrahimi, Javad Mohammadpour Velni, and Glen Rains. High-throughput cotton phenotyping big data pipeline lambda architecture computer vision deep neural networks, 2023.

[43] V. M. Ngo, N. A. Le-Khac, and M. T. Kechadi. Data warehouse and decision support on integrated crop big data, 2021.

[44] Vuong M. Ngo, Nhien-An Le-Khac, and M-Tahar Kechadi. Designing and implementing data warehouse for agricultural big data, 2019.

[45] Marco Medici, Søren Marcus Pedersen, Maurizio Canavari, Thomas Anken, Panagiotis Stamatelopoulos, Zisis Tsiropoulos, Alex Zotos, and Ghasem Tohidloo. A web-tool for calculating the economic performance of precision agriculture technology, 2020.

[46] Jun Liu and Ryan K. Williams. Monitoring over the long term: Intermittent deployment and sensing strategies for multi-robot teams, 2021.

[47] Faisal Alkaabneh and Rabiatu Bonku. Matheuristic for vehicle routing problem with multiple synchronization constraints and variable service time, 2023.

[48] Francesco Salvetti, Simone Angarano, Mauro Martini, Simone Cerrato, and Marcello Chiaberge. Waypoint generation in row-based crops with deep learning and contrastive clustering, 2022.

[49] Merrick Campbell, Amel Dechemi, and Konstantinos Karydis. An integrated actuation-perception framework for robotic leaf retrieval: Detection, localization, and cutting, 2022.

[50] Mauro Martini, Simone Cerrato, Francesco Salvetti, Simone Angarano, and Marcello Chiaberge. Position-agnostic autonomous navigation in vineyards with deep reinforcement learning, 2022.

[51] Shavbo Salehi, Jahan Hassan, and Ayub Bokani. An optimal multi-uav deployment model for uav-assisted smart farming, 2022.

[52] Jing Dong, John Gary Burnham, Byron Boots, Glen C. Rains, and Frank Dellaert. 4d crop monitoring: Spatio-temporal reconstruction for agriculture, 2016.

[53] Zhen Zhao, Yuqiu Liu, Gang Zhang, Liang Tang, and Xiaolin Hu. The winning solution to the iflytek challenge 2021 cultivated land extraction from high-resolution remote sensing image, 2022.

[54] Mahdi Maktabdar Oghaz, Manzoor Razaak, Hamideh Kerdegari, Vasileios Argyriou, and Paolo Remagnino. Scene and environment monitoring using aerial imagery and deep learning, 2019.

[55] E. C. Nunes. Employing drones in agriculture: An exploration of various drone types and key advantages, 2023.

[56] Yi-Chia Chang, Adam J. Stewart, Favyen Bastani, Piper Wolters, Shreya Kannan, George R. Huber, Jingtong Wang, and Arindam Banerjee. On the generalizability of foundation models for crop type mapping, 2025.

[57] Kui Zhao, Siyang Wu, Chang Liu, Yue Wu, and Natalia Efremova. Precision agriculture: Crop mapping using machine learning and sentinel-2 satellite imagery, 2023.

[58] Martina Mammarella, Cesare Donati, Takumi Shimizu, Masaya Suenaga, Lorenzo Comba, Alessandro Biglia, Kuniaki Uto, Takeshi Hatanaka, Paolo Gay, and Fabrizio Dabbene. 3d map reconstruction of an orchard using an angle-aware covering control strategy, 2022.

[59] Sujata Butte, Aleksandar Vakanski, Kasia Duellman, Haotian Wang, and Amin Mirkouei. Potato crop stress identification in aerial images using deep learning-based object detection, 2021.

[60] Andres Milioto, Philipp Lottes, and Cyrill Stachniss. Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in cnns, 2018.

[61] Kawsalyaa Manivannan and Bharathi Sankar. Smart farming using iot for efficient crop growth, 2023.

[62] Ali Raza, Rasool Keshavarz, and Negin Shariati. Precision agriculture: Ultra-compact sensor and reconfigurable antenna for joint sensing and communication, 2024.

[63] Virginia Strati, Matteo Alberi, Stefano Anconelli, Marica Baldoncini, Marco Bittelli, Carlo Bottardi, Enrico Chiarelli, Barbara Fabbri, Vincenzo Guidi, Kassandra Giulia Cristina Raptis, Domenico Solimando, Fausto Tomei, Giulia Villani, and Fabio Mantovani. Modelling soil water conent in a tomato field: proximal gamma ray spectroscopy and soil-crop system models, 2018.

[64] Jagruti Sahoo and Kristin Barrett. Internet of things (iot) application model for smart farming, 2021.

[65] Sabit Ahamed Preanto, Md. Taimur Ahad, Yousuf Rayhan Emon, Sumaya Mustofa, and Md Alamin. A semantic segmentation approach on sweet orange leaf diseases detection utilizing yolo, 2024.

[66] Andrea Albanese, Matteo Nardello, and Davide Brunelli. Automated pest detection with dnn on the edge for precision agriculture, 2021.

[67] Luca Crupi, Luca Butera, Alberto Ferrante, and Daniele Palossi. A deep learning-based pest insect monitoring system for ultra-low power pocket-sized drones, 2024.

[68] Balaji VS, Mahi AR, Anirudh Ganapathy PS, and Manju M. Scarecrow monitoring system:employing mobilenet ssd for enhanced animal supervision, 2024.

[69] Ilyas Potamitis. Chatgpt in the context of precision agriculture data analytics, 2023.

[70] Mikolaj Cieslak, Umabharathi Govindarajan, Alejandro Garcia, Anuradha Chandrashekar, Torsten Hädrich, Aleksander Mendoza-Drosik, Dominik L. Michels, Sören Pirk, Chia-Chun Fu, and Wojciech Pałubicki. Generating diverse agricultural data for vision-based farming applications, 2024.

[71] Zhichao Liu, Jingzong Zhou, Caio Mucchiani, and Konstantinos Karydis. Vision-assisted avocado harvesting with aerial bimanual manipulation, 2024.

[72] Alireza Ahmadi, Lorenzo Nardi, Nived Chebrolu, and Cyrill Stachniss. Visual servoing-based navigation for monitoring row-crop fields, 2019.

[73] Diego Aghi, Simone Cerrato, Vittorio Mazzia, and Marcello Chiaberge. Deep semantic segmentation at the edge for autonomous navigation in vineyard rows, 2021.

[74] Tao Liu, Baohua Zhang, Qianqiu Tan, Jun Zhou, Shuwan Yu, Qingzhen Zhu, and Yifan Bian. Immersive human-machine teleoperation framework for precision agriculture: Integrating uav-based digital mapping and virtual reality control, 2024.

[75] Giorgio Morales and John Sheppard. Counterfactual analysis of neural networks used to create fertilizer management zones, 2024.

[76] Steph Rudd and Hamish Cunningham. Selective privacy in iot smart-farms for battery-powered device longevity, 2021.

[77] Mary Adkisson, Jeffrey C Kimmel, Maanak Gupta, and Mahmoud Abdelsalam. Autoencoder-based anomaly detection in smart farming ecosystem, 2021.

[78] Flavio Piccoli, Simone Locatelli, Paolo Napoletano, and Raimondo Schettini. A unified platform for gis data management and analytics, 2022.

[79] Vuong M. Ngo, Nhien-An Le-Khac, and M-Tahar Kechadi. An efficient data warehouse for crop yield prediction, 2018.

[80] Md. Rashid Al Asif, Khondokar Fida Hasan, Md Zahidul Islam, and Rahamatullah Khondoker. Stride-based cyber security threat modeling for iot-enabled precision agriculture systems, 2022.

[81] Inkyu Sa, Marija Popovic, Raghav Khanna, Zetao Chen, Philipp Lottes, Frank Liebisch, Juan Nieto, Cyrill Stachniss, Achim Walter, and Roland Siegwart. Weedmap: A large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming, 2018.

[82] Akshay L Chandra, Sai Vikas Desai, Wei Guo, and Vineeth N Balasubramanian. Computer vision with deep learning for plant phenotyping in agriculture: A survey, 2020.

[83] Alireza Ghanbari, Gholamhassan Shirdel, and Farhad Maleki. Semi-self-supervised domain adaptation: Developing deep learning models with limited annotated data for wheat head segmentation, 2024.

[84] Grigore Stamatescu, Cristian Dragana, Iulia Stamatescu, Loretta Ichim, and Dan Popescu. Iot-enabled distributed data processing for precision agriculture, 2019.

[85] Samuel Matloob, Partha P. Datta, O. Patrick Kreidl, Ayan Dutta, Swapnoneel Roy, and Ladislau Bölöni. Waterberry farms: A novel benchmark for informative path planning, 2023.

[86] Pooyan Abouzar, David G. Michelson, and Maziyar Hamdi. Rssi-based distributed self-localization for wireless sensor networks used in precision agriculture, 2015.

[87] Nadia Delavarpour, Cengiz Koparan, John Nowatzki, Sreekala Bajwa, and Xin Sun. A technical study on uav characteristics for precision agriculture applications and associated practical challenges. *Remote Sensing*, 13(6):1204, 2021.

[88] Ramakant Kumar. Transforming agriculture: Exploring diverse practices and technological innovations, 2024.

[89] Lukas Schulthess, Fabrice Longchamp, Christian Vogt, and Michele Magno. A lora-based and maintenance-free cattle monitoring system for alpine pastures and remote locations, 2024.

[90] Diego Aghi, Vittorio Mazzia, and Marcello Chiaberge. Local motion planner for autonomous navigation in vineyards with a rgb-d camera-based algorithm and deep learning synergy, 2020.

[91] Yaoqiang Pan, Kewei Hu, Tianhao Liu, Chao Chen, and Hanwen Kang. Pheno-robot: An auto-digital modelling system for in-situ phenotyping in the field, 2024.

[92] Giulio Reina, Annalisa Milella, and Rocco Galati. Terrain assessment for precision agriculture using vehicle dynamic modelling, 2021.

[93] Uzair Aslam Bhatti, Mehdi Masud, Sibghat Ullah Bazai, and Hao Tang. Investigating ai-based smart precision agriculture techniques, 2023.

[94] Ashwin Natraj Arun, Byunghyun Lee, Fabio A. Castiblanco, Dennis R. Buckmaster, Chih-Chun Wang, David J. Love, James V. Krogmeier, M. Majid Butt, and Amitava Ghosh. Ambient iot: Communications enabling precision agriculture, 2024.

[95] Harry Rogers, Tahmina Zebin, Grzegorz Cielniak, Beatriz De La Iglesia, and Ben Magri. Deep learning for precision agriculture: Post-spraying evaluation and deposition estimation, 2024.

[96] Thomas A. Ciarfuglia, Ionut M. Motoi, Leonardo Saraceni, Mulham Fawakherji, Alberto Sanfeliu, and Daniele Nardi. Weakly and semi-supervised detection, segmentation and tracking of table grapes with limited and noisy data, 2023.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.