



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2025): 5.20
www.agronomyjournals.com
2025; SP-8(11): 276-282
Received: 19-08-2025
Accepted: 22-09-2025

Nishan Patil
Scientist and Head, Farm
Machinery & Power Engineering,
Vasantdada Sugar Institute,
Manjari, Haveli, Pune,
Maharashtra, India

Sandeep Sankpal
Vasantdada Sugar Institute,
Manjari, Haveli, Pune,
Maharashtra, India

Himanshu Madavi
Project Executive, Wildlife
Research & Conservation Society,
Koynanagar Division, Satara,
Maharashtra, India

Corresponding Author:
Nishan Patil
Scientist and Head, Farm
Machinery & Power Engineering,
Vasantdada Sugar Institute,
Manjari, Haveli, Pune,
Maharashtra, India

Advances in precision agriculture: Integrating AI, Drones, IoT and GIS for efficient water, nutrients management and plant protection

Nishan Patil, Sandeep Sankpal and Himanshu Madavi

DOI: <https://www.doi.org/10.33545/2618060X.2025.v8.i11Sd.4257>

Abstract

The global agricultural sector faces critical pressures from unprecedented population growth and intensifying environmental instability, necessitating a paradigm shift towards sustainable intensification and highly efficient resource management. Precision Agronomy (PA), leveraging the synergistic integration of advanced technologies, provides the necessary data-driven framework for site-specific resource optimization. This systematic review examines the unified architectural framework where the Internet of Things (IoT) and Drones (UAVs) serve as the real-time and high-resolution data acquisition layers. Geographic Information Systems (GIS) provide the critical spatial intelligence for data fusion, spatial interpolation (e.g., Kriging), and the delineation of Site-Specific Management Zones (SSMZs). Artificial Intelligence (AI) algorithms, including Machine Learning (ML) like XGBoost and Deep Learning (DL) architectures like CNN-GRU, translate this fused spatio-temporal data into optimized, actionable Variable Rate Application (VRA) prescriptions for nutrients and water. The evidence confirms the transformative impact of this integrated approach on resource efficiency and productivity: Precision Nutrient Management (PNM) demonstrates concurrent gains of up to a 17% increase in crop yield and a 23% reduction in fertilizer usage, while intelligent irrigation systems achieve water consumption savings of up to 50%. Despite these proven technical and economic benefits, widespread adoption is significantly hampered by high up-front acquisition costs, a critical lack of standardized interoperability between diverse technologies, and profound farmer concerns regarding data privacy, security, and ownership. Future research directions prioritize developing holistic Digital Twins for complex, dynamic simulation and utilizing Reinforcement Learning for adaptive, autonomous decision support, ensuring the continuous evolution toward sustainable and resilient farming practices.

Keywords: AI, Drones, IoT, GIS, smart nutrient, precision agronomy

1. Introduction

1.1. Context and Global Imperative

The global agricultural system faces a critical inflection point driven by two primary pressures: unprecedented demographic growth and intensifying environmental instability. The necessity for advanced and efficient farming practices has become paramount, particularly as the world population is projected to reach 10 billion by 2050. Traditional, uniform farming methods are increasingly recognized as environmentally unsustainable and inherently inefficient, yielding low gross margins due to indiscriminate application of inputs.

The response lies in shifting towards sustainable intensification a pathway fundamentally enabled by the precise management of critical resources, namely water and nutrients. The structural role of agriculture in economic growth is well-established; improvements in agronomic inputs, such as fertilizer and water, are linked to significant yield increases, which subsequently correlate with higher Gross Domestic Product (GDP) per capita (Johnston & Mellor, 1961; Schultz, 1968) ^[17, 42]. Precision Agronomy (PA) offers the data-driven framework essential for realizing these ecological and economic gains.

1.2. The Evolution and Paradigm Shift to Precision Agronomy 4.0

Precision Agriculture has undergone significant technological evolution, moving from early

conceptual stages to the highly automated, data-centric discipline known today as Agriculture 4.0 or "smart farming". This modern era, established around 2017, is defined by the pervasive integration of Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics.

This integrated technological framework facilitates a paradigm shift from broad-acre management to site-specific management, supporting the four foundational pillars of PA: applying the right practice, at the right place, at the right time, and with the right quantity. The synergistic relationship among AI, Drones, IoT, and Geographic Information Systems (GIS) provides the data acquisition, spatial analysis, and predictive power needed to manage crop inputs efficiently and sustainably.

1.3. Scope and Structure of the Review

This paper provides a systematic review of the integrated technological architecture used in contemporary precision agronomy. It critically examines the mechanisms of synergy among AI, Unmanned Aerial Vehicles (UAVs/Drones), IoT sensor networks, and GIS platforms. The review focuses specifically on how this unified framework drives optimization in site-specific Precision Nutrient Management (PNM) and Precision Water Management (PWM). Key areas of analysis include the technological requirements for data fusion, quantitative performance metrics of integrated systems, key barriers to widespread adoption, and promising future research pathways.

2. Foundational Technologies and Architectural Synergy

The successful implementation of Precision Agronomy hinges on the seamless integration of technologies operating across three distinct layers: data acquisition (IoT and Drones), spatial analysis (GIS), and intelligence (AI) (Fig 1).

2.1. The Internet of Things (IoT) Ecosystem: The Data Acquisition Layer

The IoT ecosystem forms the foundational physical layer for real-time agricultural monitoring. This architecture relies on robust Wireless Sensor Networks (WSN) comprising smart sensors that continuously collect critical environmental data, including soil moisture, pH, Electrical Conductivity (EC), and meteorological conditions. This high-frequency, time-series data is transmitted to cloud platforms for subsequent analysis and processing.

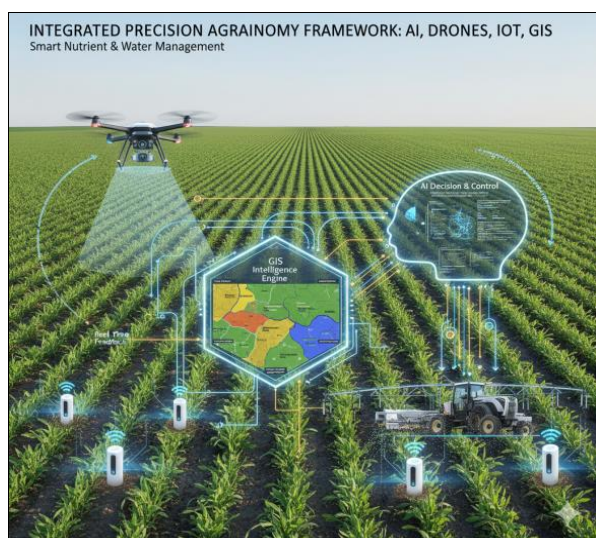


Fig 1: The Integrated Precision Agronomy Framework

The architectural requirements for IoT deployment in large-scale agriculture necessitate robustness, scalability, and high data throughput. Advancements in communication technologies, such as 5G, LoRaWAN, NB-IoT, and ZigBee, have broadened the application range of IoT, providing the necessary bandwidth and coverage required to minimize latency and ensure successful data communication in remote agricultural areas (Kamilaris *et al.*, 2024) ^[19]. The continuous data stream provided by this layer is essential for creating dynamic, automated irrigation and fertilization schedules, which are instrumental in reducing water waste and maximizing efficiency (Sinha, 2024) ^[46].

2.2. Drones (UAVs) and Remote Sensing: High-Resolution Spatial Input

Unmanned Aerial Vehicles (UAVs), commonly known as drones, act as mobile sensor platforms, providing the high-resolution spatial data necessary for site-specific management. UAVs offer distinct operational advantages over traditional satellite imagery, notably superior spatial and temporal resolution, greater flexibility in deployment, and the ability to capture data reliably despite cloud cover (Yousif, 2024) ^[52].

Drone platforms are equipped with cutting-edge sensor payloads, including thermal cameras, RGB imagers, and, most critically, multispectral and hyperspectral sensors. These sophisticated sensors generate imagery used to derive key diagnostic outputs, such as Vegetation Indices (VIs). Indices like the Normalized Difference Vegetation Index (NDVI) and Red-Edge Chlorophyll Index (RECI) are direct, quantitative indicators of plant health, growth stage, water stress, and nutrient deficiencies. The integration of these high-resolution indices with advanced AI analytics facilitates significant operational improvements, such as early detection of diseases and precise yield estimation (Sharma, 2024) ^[44].

2.3. Geographic Information Systems (GIS): The Spatial Intelligence Engine

GIS serves as the indispensable spatial framework, integrating and synthesizing the massive, multi-layered, and heterogeneous datasets collected from IoT sensors, UAVs, and farm machinery. GIS facilitates the georeferencing, storage, analysis, and visualization of this complex information, enabling the identification and quantification of field variability (Zhao, 2021) ^[53].

Kriging and Spatial Interpolation

To transform sparse point data collected by ground sensors (e.g., soil samples) into continuous, usable field maps, GIS programs rely on advanced spatial modeling techniques. Kriging is established as a critical interpolation method for generating foundational variability maps, particularly for soil properties like nitrogen (N) or electrical conductivity (EC). Unlike simpler interpolation methods, Kriging is an optimal linear predictor that utilizes the spatial correlation (autocorrelation) between sampled points. This approach minimizes the prediction error for each interpolated value and reduces bias resulting from clustered sampling patterns, thereby generating the Best Linear Unbiased Predictors (BLUPs) necessary for accurate site-specific planning.

Delineation of Management Zones (SSMZs)

The primary output of the GIS analysis layer is the delineation of Site-Specific Management Zones (SSMZs). SSMZs divide a field into areas with similar soil, topographical, or yield characteristics, allowing customized resource treatments. These

zones are typically identified through cluster analysis techniques (e.g., using Management Zone Analyst, MZA software) or through advanced machine learning approaches such as Artificial Neural Networks (ANN). The delineation process identifies key yield-limiting factors, which may include specific soil properties (e.g., organic matter, phosphorus, magnesium), canopy parameters, or elevation data, enabling the generation of maps for variable rate application (Kim, 2024).

The effectiveness of the final resource Prescription Map (PM) relies heavily on the GIS engine's ability to accurately harmonize diverse data types. The system must efficiently interpolate the sparse, high-temporal-density point data provided by the IoT network (using methods like Kriging) and integrate it with the comprehensive, high-resolution spatial coverage data derived from drone VIs. This ensures that prescriptions account for both instantaneous environmental conditions and inherent soil variability. Furthermore, while map-based Variable Rate Application (VRA) systems, which rely on GIS and interpolation, provide the strategic, long-term prescription, the future of PA requires convergence with sensor-based VRA systems (Madondo, 2023) ^[26]. This involves autonomous ground robots and other mobile sensor platforms executing the map-based prescription while simultaneously collecting high-resolution, plant-level, under-canopy data. This real-time, site-specific monitoring feeds back into the system, continuously validating and refining the next generation of management zone maps, thereby closing the data loop and enhancing long-term operational accuracy (Porkodi, 2024) ^[33].

3. Artificial Intelligence and Data Fusion for Decision Making

Artificial Intelligence (AI), encompassing Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), serves as the intelligence layer, translating fused geospatial and temporal data into actionable resource management decisions.

3.1. Machine Learning for Predictive Soil and Nutrient Modeling

Machine Learning models are essential for extracting actionable insights from the complex datasets generated by IoT and UAV platforms. ML algorithms excel at predicting optimal resource levels based on environmental covariates, enabling site-specific fertilization. In studies focused on optimizing fertilizer application, ensemble methods consistently demonstrate high performance. Specifically, the XGBoost model has achieved superior results, reporting an accuracy of 93.4% in predicting the optimal fertilizer type and dosage when analyzing key agronomic parameters, including soil nutrients (N, P, K), pH, organic carbon, weather conditions, and crop type (Saki, 2025) ^[39].

ML techniques are also vital for continuous soil health monitoring and yield forecasting. For instance, the LightGBM classifier has been used to analyze macronutrients, achieving an accuracy of 95.56% in identifying complex relationships between soil nutrients and health indicators (Sharma *et al.*, 2024) ^[44]. This capability empowers farmers to optimize fertilizer use precisely, ensuring nutrient balance and boosting crop yields. Furthermore, advanced predictive models are necessary to overcome the hurdles of accurate crop yield prediction, which requires integrating multiple factors such as climate, soil characteristics, and localized farming practices (Prabavathi & Chelliah, 2022; Mgendi, 2024) ^[28, 34].

3.2. Deep Learning for Spatio-Temporal Forecasting

Deep Learning (DL) architectures are necessitated by the inherent complexity of agricultural data, which exhibits high dimensionality and strong spatial-temporal dependencies that traditional time series models struggle to manage.

CNNs and RNNs in Data Processing

Convolutional Neural Networks (CNNs) are employed for high-accuracy spatial tasks, primarily image processing of aerial data. CNNs are utilized for crop monitoring, object detection, and image segmentation, especially for distinguishing weeds from crops using multispectral data and vegetation indices. Meanwhile, Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are crucial for handling sequential IoT and meteorological data, enabling precise forecasting of water requirements and climate impacts (El Sakka, 2025) ^[10].

Hybrid Architectures for Data Fusion

State-of-the-art research emphasizes hybrid DL frameworks to maximize performance. The need for these complex architectures stems directly from the heterogeneity of the fused data. Simple, standalone models cannot adequately process the high dimensionality introduced by combining dense drone spectral bands, continuous IoT time-series inputs, and static geospatial covariates (elevation, soil type). Hybrid models, such as integrated CNN-RNN structures, address this challenge by separating spatial feature extraction (CNN) from temporal dependency modeling (GRU/LSTM) before fusing the results (Zhao, 2021) ^[53]. For instance, a 2D CNN-GRU model leveraging high-resolution Sentinel-2 red-edge bands achieved an overall accuracy of 99.12% in challenging crop classification tasks within mixed agricultural regions (Sher, 2024) ^[45].

3.3. Reinforcement Learning (RL) for Adaptive Decision Support

The integration of AI must progress beyond mere static prediction to dynamic adaptation. While ML (e.g., XGBoost) provides an accurate *prediction* of nutrient requirements, and GIS generates a static *prescription* map, the core value lies in creating systems that can dynamically learn and adapt to real-time field responses (Akintuyi, 2024) ^[1].

Advanced frameworks, such as the Spatially-Aware Data Fusion Network (SADF-Net), formally integrate multi-modal data streams by combining convolutional layers, recurrent layers (GRUs), and attention mechanisms to capture intricate spatial-temporal dependencies. Crucially, the Resource-Aware Adaptive Decision Algorithm (RAADA) leverages Reinforcement Learning (RL) to interpret SADF-Net's predictions and translate them into optimized, dynamic resource allocation strategies, such as irrigation scheduling and pest control (Chen, 2023) ^[7]. This adaptation mechanism is essential for mitigating risks associated with rapidly changing environmental conditions (e.g., unpredicted weather events), effectively closing the loop between the initial resource prescription and the actual environmental outcome (He, 2025) ^[15].

4. Applications and Quantitative Performance in Smart Resource Management

The integration of AI, Drones, IoT, and GIS culminates in Variable Rate Application (VRA) technology, the physical embodiment of site-specific management (Table 1).

Table 1: Integrated Technological Architecture for Precision Agronomy

Technology Layer	Core Function	Key Hardware/Data Inputs	Decision Output	Reference
IoT & Sensor Networks	Real-Time Environmental Monitoring	Soil moisture probes, pH/EC sensors, Weather stations	High-frequency, temporal data streams for modeling	Mansoor, 2025 ^[27] . Kumari <i>et al.</i> (2025) ^[24] .
Drones (UAVs) & Remote Sensing	High-Resolution Spatial Mapping	Multispectral/Hyperspectral sensors, RGB, LiDAR	Vegetation Indices (NDVI, RECI), Digital Elevation Models (DEMs)	Pan <i>et al.</i> (2023) ^[32] . Wang <i>et al.</i> (2025) ^[51] .
GIS & Spatial Analytics	Data Fusion and Zone Delineation	Kriging Interpolation (e.g., soil N/EC), SSMZ clustering (MZA, ANN)	Geospatial Variability Maps, Management Zone Polygons	Yousif <i>et al.</i> (2024) ^[52] . Bhagwan <i>et al.</i> (2025) ^[5] .
AI/ML/DL	Predictive/Adaptive Modeling	ML (XGBoost) for nutrient dosage; DL (CNN-GRU/LSTM) for forecasting	Optimized Resource Recommendations (Rate, Timing, Location)	Dey, 2024 ^[9] Wang, 2023 ^[49]

4.1. Precision Nutrient Management (PNM)

Precision Nutrient Management relies on VRA to apply inputs like fertilizers, lime, and seeds precisely where needed. Prescription maps, generated by fusing GIS spatial analysis (e.g., anagement zones) with AI-derived recommendations, control variable fertilization applicators (Sadhukhan, 2023) ^[38].

Economic and Environmental Benefits

The most compelling validation of PNM is its ability to achieve concurrent yield increases and input reductions, demonstrating dual optimization. A study utilizing the XGBoost model for optimal nitrogen application reported a significant 17% increase in average crop yield and a simultaneous 23% reduction in fertilizer usage compared to traditional uniform application methods (Saki, 2025; Kumar, 2022) ^[23, 39]. More generally, AI-based soil nutrient analysis systems report a typical range of 10–20% reduction in input costs and a corresponding 15–25% increase in crop yields (Gangwani, 2024) ^[11]. Economically, Variable Rate Technology (VRT) provides a foundation for climate protection and fiscal benefits. For farmers, the Return on Investment (ROI) averages between 20 and 50 per acre under favorable conditions, with break-even often achieved within two to three years. Environmentally, VRA ensures precise input application, reducing waste and pollution. By minimizing over-application, PNM significantly lowers nutrient runoff and leaching, directly protecting water bodies and reducing the carbon footprint of agriculture, contributing to a reported 20% reduction in CO2 emissions (Gupta, 2025) ^[14]. This supports global objectives such as Clean Water and Sanitation (SDG 6) and Climate Action (SDG 13).

4.2. Precision Water Management (PWM)

Precision Water Management (PWM), often referred to as

Precision Irrigation Systems (PISs), is a highly recommended approach to mitigate global water crises and enhance Water Use Efficiency (WUE). PWM systems rely on AI models that integrate real-time soil moisture sensor data with weather forecasts and evapotranspiration rates to create dynamic irrigation schedules that prevent overwatering and nutrient loss (Lakhia, 2024) ^[25].

Water Savings and Efficiency

The application of AI in irrigation has the ability to efficiently reduce water usage, improve agricultural yields, and reduce associated environmental impacts (Sinha, 2024) ^[46]. Quantitative analysis shows that intelligent irrigation systems increase the efficiency of water consumption by 15.6% compared to conventional flood irrigation. The most advanced AI-driven systems demonstrate the potential for substantial resource optimization, achieving water savings of up to 50% (Gupta, 2025) ^[14]. Integrated IoT architectures, such as those implemented in the SWAMP project, successfully address the challenges of seamless integration and scalability for efficient irrigation water resource management (Table 2). Systems utilizing field sensors (e.g., W-Tens) and remote sensing (e.g., IRRISAT®) excel in Irrigation Water Use Efficiency (IWUE), confirming the superior performance of integrated tools (Kim, 2024). Furthermore, the network of IoT sensors deployed for PWM also provides a critical environmental feedback mechanism. Beyond just controlling irrigation volume, the same technology stack can monitor water quality parameters (e.g., pH, salinity) in drainage or surface water (Hui *et al.*, 2020) ^[16]. This capability allows agronomists to quantitatively measure the reduction in chemical runoff resulting from precision fertilization, thereby validating the environmental benefits claimed by the integrated PA system (Schimmelpfennig, 2018) ^[40].

Table 2: Quantitative Performance and Economic Outcomes of Integrated PA Systems

Resource Management Focus	Technology/Algorithm Used	Reported Efficiency Gain	Economic/Environmental Benefit	Key Source
Nutrient Management (Fertilizer)	ML/VRA (XGBoost)	17% increase in average crop yield	23% reduction in fertilizer usage	Porkodi, 2024 ^[33]
Nutrient Management (General)	AI-Based Soil Analysis	15 - 25% increase in crop yields	15–20% reduction in input costs	(Lakhia, 2024) ^[25]
Water Management (Irrigation)	Precision Irrigation Systems (PIS)	15.6% increased water efficiency	Reduces runoff (SDG 6)	(Lakhia, 2024) ^[25]
Water Management (Irrigation)	AI-Driven Systems	Up to 50% water savings	Enhanced economic viability	(Gupta, 2025) ^[14]
Environmental Sustainability	Integrated PA		20% reduction in CO2 emissions	(Bahmutsky, 2024) ^[4]

5. Challenges, Barriers, and Economic Viability

Despite the demonstrated technical success and quantitative benefits, the widespread adoption of integrated precision

agronomy systems faces multifaceted challenges spanning economic, governance, and technical domains.

5.1. Economic and Financial Barriers to Adoption

The most significant immediate barrier is the high up-front acquisition cost associated with advanced precision equipment, including high-resolution sensors, VRA machinery, and autonomous vehicles (Schimmelpfennig, 2018) ^[40]. The realization of a positive Return on Investment (ROI) is highly dependent on localized conditions. Analysis indicates that VRA profitability is inconsistent, with results ranging from negative returns (up to – 410/ha in poor seasons) to substantial profit (up to 350/ha) (Robertson, 2012) ^[35].

The fundamental economic decision to adopt VRA is contingent upon the existing degree of field variability; fields with high inherent variability demonstrate a strong ROI due to better resource allocation, whereas fields with low variability show only marginal returns (Bramley, 2019) ^[6].

Furthermore, the benefits of PA are inequitably distributed due to socio-economic segmentation. Adoption is shallow among smallholder farmers, particularly in developing regions, primarily due to the prohibitive initial costs and a lack of technical expertise. Research shows that larger farm size and longer farming experience increase the likelihood of PA adoption, while older farmer age negatively affects it. Targeted interventions, including financial support and developing technology customized for smaller-scale operations, are essential for democratizing access (Mizik, 2023) ^[30].

5.2. Data Governance, Security, and Trust Deficit

The foundation of data-driven agriculture relies on the continuous collection and analysis of voluminous field data. This reliance introduces severe issues related to data governance and trust. Farmers express profound concerns regarding the security and privacy of their proprietary data, fearing unauthorized access, collection, and sharing with Agricultural Technology Providers (ATPs). These concerns also include the potential loss of competitive advantage and the risk of additional regulatory scrutiny as AI is increasingly used for detailed data analysis (Jouanjean, 2020) ^[18].

This prevailing trust deficit represents a critical non-technical barrier. If farmers lack confidence in transparent data use agreements, they may refuse or restrict data sharing, which inherently limits the quality and volume of input data necessary for AI models to scale and perform optimally (e.g., highly accurate NDVI-based VRA maps require consistent data input) (Kaur, 2022) ^[20].

Moreover, the widespread deployment of IoT devices in agriculture introduces security vulnerabilities due to a lack of standardized security protocols across diverse hardware manufacturers. Implementing Edge Computing, which processes data locally rather than centrally on cloud platforms, is emerging as a critical mitigation strategy. Edge computing reduces latency and enhances security by minimizing the potential attack surface of the IoT ecosystem (Gong, 2025) ^[12].

5.3. Technical and Regulatory Hurdles

Technical limitations persist, particularly the pervasive absence of uniform standards. The lack of standardized protocols hampers interoperability between precision agriculture technologies from different manufacturers, complicating integration and challenging the consistent assessment of fused data quality. Policymakers and industry organizations must prioritize mandating standards compliance, especially for equipment covered under financial assistance programs, to promote a coherent PA ecosystem (Roccatello, 2025) ^[37].

Furthermore, while automation is increasing, the complexity of integrated systems still places substantial requirements on

human capital. Technical problems and the necessity for continuous support and training are identified barriers to successful integration (Neetye, 2023) ^[31].

Finally, the full operational potential of drone technology remains constrained by regulatory obstacles. Specifically, the need to harmonize regulations governing Beyond Visual Line of Sight (BVLOS) flights must be addressed to facilitate scalable operations, such as drone swarms (Guebsi, 2024) ^[13].

6. Future Directions and Emerging Technologies

The trajectory of precision agronomy points toward greater autonomy, integration, and predictive capability, driven by advanced computational paradigms.

6.1 Advanced AI/ML Paradigms

Future research will intensify the focus on advanced AI techniques that enable true autonomy. Reinforcement Learning (RL) is key to this transition, moving systems beyond static prescriptions to dynamically optimizing resource management strategies (like irrigation and fertilization) based on learning from real-time environmental feedback (Wang, 2025) ^[50].

Additionally, Generative Adversarial Networks (GANs) are being explored to enhance the training sets for specialized agricultural AI. GANs can synthesize realistic data for rare events, such as specific disease symptoms, improving the adaptability and operational efficiency of autonomous AI systems (Madondo, 2023) ^[26].

6.2 Robotics, Automation and Sensor Development for Disease Management

Precision agronomy is evolving beyond nutrient and water management to active disease management, leveraging robotics, automation and advanced sensors to detect, map, and respond to crop diseases in real-time.

6.2.1 Autonomous Platforms for Disease Monitoring and Response

Autonomous ground vehicles (UGVs) and aerial drone swarms are increasingly used as mobile sensor platforms for under-canopy phenotyping, early disease detection, and localized treatment intervention (Reina *et al.*, 2024) ^[35]. For example, an AI-based drone system demonstrated accurate multi-class plant disease detection by integrating multispectral imagery and machine learning for automatic diagnosis and timely treatments (Albattah *et al.*, 2022) ^[2].

Ali *et al.*, (2024) ^[3] Further, UAV-swarm approaches have been applied for monitoring plant health, nutrition disorders and disease outbreaks in large crop areas, confirming the viability of robotic platforms for disease surveillance. These systems enable ultra-high resolution spatial mapping of disease symptoms, supporting precision interventions such as targeted spraying, thus reducing chemical usage and limiting disease spread.

6.2.2 Sensor Miniaturisation, IoT and Edge Analytics for Disease Detection

The integration of IoT sensors with miniaturised platforms allows real-time detection of plant-stress indicators (e.g., leaf moisture, chlorophyll fluorescence, stomatal conductance) which are early signals of pathogen invasion or disease onset. A recent review highlighted how IoT-enabled sensors, combined with AI and machine-learning models, support predictive disease management by continuously monitoring field micro-climate, plant health and soil conditions (Delfani, 2024) ^[8]. Edge computing architectures further enhance this capability by processing data locally on sensor nodes or mobile platforms,

reducing latency, improving responsiveness and increasing security of sensitive on-farm disease data (Miller *et al.*, 2025)^[29].

6.2.3 Spectral Indices, Multispectral/Hyperspectral Imaging and Deep Learning

Advanced sensors on UAVs and UGVs capture multispectral and hyperspectral data which can be processed via deep-learning models to identify disease symptoms even before they become visually apparent. One large-scale survey of UAV-based crop disease detection found that combining high-resolution imagery, convolutional neural networks and vegetation indexes significantly improved early detection accuracy relative to manual inspection (Shahi *et al.*, 2023)^[43]. In another work by Upadhyay *et al.*, (2025)^[47], deep-learning-based image analysis of plant disease achieved strong classification performance across diverse crops and symptoms, confirming the role of DL in automated disease diagnosis. These technologies support the creation of disease-specific management zone maps, enabling variable-rate fungicide or bactericide applications tailored to symptom severity and spatial distribution.

6.2.4 Towards Integration: Closed-Loop Disease Management Framework

The future of disease management in precision agriculture lies in closed-loop systems where detection, decision-making, and intervention are automated. Mobile robotic platforms gather high-resolution disease data, onboard analytics determine treatment zones and variable-rate applicators deploy precise fungicide or biocontrol treatments. The system then monitors outcomes and adjusts strategies dynamically. This integrated automation supports better ROI certainty, reduces chemical use and enhances system resilience to rapid disease outbreaks. While full-scale commercial adoption remains limited, research indicates that fields with high variability in disease distribution benefit the most from robotic and sensor-driven disease management (Delfani *et al.*, 2024)^[8].

7. Conclusion

The integration of AI, Drones, IoT, and GIS has successfully established a robust, data-driven framework for Precision Agronomy. This framework systematically collects high-resolution spatial (UAV/GIS) and high-frequency temporal (IoT) data, utilizes advanced AI/ML algorithms (e.g., XGBoost, CNN-GRU) for predictive modeling, and culminates in the economic and environmental efficiency of Variable Rate Application (VRA). Quantitative evidence confirms the efficacy of this approach, demonstrating concurrent gains in productivity (up to 25% yield increase) and substantial reductions in resource consumption (up to 50% water savings and 23% fertilizer reduction).

However, the widespread proliferation of this technology is significantly constrained by a triad of challenges. Firstly, the high initial acquisition cost restricts accessibility, particularly for smallholder farms. Secondly, the lack of standardized interoperability among devices complicates integration and undermines data reliability. Thirdly, a critical non-technical barrier is the crisis of farmer trust regarding data ownership, privacy, and security in the burgeoning agricultural technology ecosystem.

Moving forward, research must prioritize the development of adaptive, self-optimizing systems leveraging Digital Twins and Reinforcement Learning to handle real-world uncertainties and maximize the reliability of the Return on Investment. Concurrently, policy interventions must focus on financial

support mechanisms, mandatory technical standards for interoperability, and the establishment of clear, transparent legal frameworks for data governance to ensure that the transformative benefits of Precision Agronomy are equitable and globally accessible.

Conflict of Interest

The authors declare no conflict of interest. This review was conducted independently, and no financial support, personal relationships, or affiliations could have appeared to influence the content or conclusions presented in this manuscript.

References

1. Akintuyi OB. Adaptive AI in precision agriculture: a review: investigating the use of self-learning algorithms in optimizing farm operations based on real-time data. *Res J Multidiscip Stud.* 2024;7(02):16-30.
2. Albattah W, Javed A, Nawaz M, Masood M, Albahli S. Artificial intelligence-based drone system for multiclass plant disease detection using an improved efficient convolutional neural network. *Front Plant Sci.* 2022;13:808380.
3. Ali ZA, Deng D, Shaikh MK, Hasan R, Khan MA. AI Based UAV swarms for monitoring and disease identification of Brassica plants using machine learning: a review. *Comput Syst Sci Eng.* 2024;48(1).
4. Bahmutsky S, Grassauer F, Arulnathan V, Pelletier N. A review of life cycle impacts and costs of precision agriculture for cultivation of field crops. *Sustain Prod Consum.* 2024;52:347-62.
5. Bhagwan PV, Anjaiah T, Ravali C, Devi MU, Neelima TL, Chary DS, *et al.* Delineating soil fertility management zones using geostatistics and fuzzy clustering in semi-arid maize systems in India. *Environ Monit Assess.* 2025;197(11):1-26.
6. Bramley RGV, Ouzman J. Farmer attitudes to the use of sensors and automation in fertilizer decision-making: nitrogen fertilization in the Australian grains sector. *Precis Agric.* 2019;20(1):157-75.
7. Chen Y, Yu Z, Han Z, Sun W, He L. A decision-making system for cotton irrigation based on reinforcement learning strategy. *Agronomy.* 2023;14(1):11.
8. Delfani P, Thuraga V, Banerjee B, Chawade A. Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change. *Precis Agric.* 2024;25(5):2589-613.
9. Dey B, Ferdous J, Ahmed R. Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables. *Heliyon.* 2024;10(3).
10. El Sakka M, Ivanovici M, Chaari L, Mothe J. A review of CNN applications in smart agriculture using multimodal data. *Sensors.* 2025;25(2):472.
11. Gangwani N. AI-driven precision agriculture: optimizing crop yield and resource efficiency. *Computer.* 2024;6(1).
12. Gong R, Zhang H, Li G, He J. Edge computing-enabled smart agriculture: technical architectures, practical evolution, and bottleneck breakthroughs. *Sensors.* 2025;25(17):5302.
13. Guebsi R, Mami S, Chokmani K. Drones in precision agriculture: a comprehensive review of applications, technologies, and challenges. *Drones.* 2024;8(11):686.
14. Gupta G, Kumar Pal S. Applications of AI in precision agriculture. *Discov Agric.* 2025;3(1):61.
15. He T, Li M, Jin D. Deep learning-based time series prediction for precision field crop protection. *Front Plant*

- Sci. 2025;16:1575796.
16. Hui Y, Huang Z, Alahi MEE, Nag A, Feng S, Mukhopadhyay SC. Recent advancements in electrochemical biosensors for monitoring water quality. *Biosensors*. 2022;12(7):551.
 17. Johnston BF, Mellor JW. The role of agriculture in economic development. *Am Econ Rev*. 1961;51(4):566-93.
 18. Jouanjan MA, Casalini F, Wiseman L, Gray E. Issues around data governance in the digital transformation of agriculture: the farmers' perspective. 2020.
 19. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. *Comput Electron Agric*. 2018;147:70-90.
 20. Kaur J, Hazrati Fard SM, Amiri-Zarandi M, Dara R. Protecting farmers' data privacy and confidentiality: recommendations and considerations. *Front Sustain Food Syst*. 2022;6:903230.
 21. Kim TH, AlZubi AA. AI-enhanced precision irrigation in legume farming: optimizing water use efficiency. *Legume Res*. 2024;47(8):1382-9.
 22. Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital twin in manufacturing: a categorical literature review and classification. *IFAC-PapersOnLine*. 2018;51(11):1016-22.
 23. Kumar A, Sharma H, Kumar S. AI-based soil fertility management review: challenges and opportunities. *J Survey Fish Sci*. 2022;8(2):283-88.
 24. Kumari S, Ali N, Dagati M, Dong Y. IoT-enabled soil moisture and conductivity monitoring under controlled and field fertigation systems. *AgriEngineering*. 2025;7(7):207.
 25. Lakhiar IA, Yan H, Zhang C, Wang G, He B, Hao B, *et al*. A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. *Agriculture*. 2024;14(7):1141.
 26. Madondo M, Azmat M, Dipietro K, Horesh R, Jacobs M, Bawa A, *et al*. A SWAT-based reinforcement learning framework for crop management. *arXiv*. 2023;2302.04988.
 27. Mansoor S, Iqbal S, Popescu SM, Kim SL, Chung YS, Baek JH. Integration of smart sensors and IoT in precision agriculture: trends, challenges and future prospectives. *Front Plant Sci*. 2025;16:1587869.
 28. Mgendi G. Unlocking the potential of precision agriculture for sustainable farming. *Discov Agric*. 2024;2(1):87.
 29. Miller T, Mikiciuk G, Durluk I, Mikiciuk M, Łobodzińska A, Śnieg M. The IoT and AI in agriculture: the time is now—a systematic review of smart sensing technologies. *Sensors*. 2025;25(12):3583.
 30. Mizik T. How can precision farming work on a small scale? A systematic literature review. *Precis Agric*. 2023;24(1):384-406.
 31. Neeteye HS. An investigation of change in drone practices in broadacre farming environments. 2023.
 32. Pan W, Wang X, Sun Y, Wang J, Li Y, Li S. Karst vegetation coverage detection using UAV multispectral vegetation indices and machine learning algorithm. *Plant Methods*. 2023;19:7.
 33. Porkodi J, Selvi BK, Nagavaratharajan A. Precision agriculture: forecasting plant nutrient requirements with machine learning. *Ecol Environ Conserv*. 2024;30.
 34. Prabavathi R, Chelliah BJ. A comprehensive review on machine learning approaches for yield prediction using essential soil nutrients. *Univ J Agric Res*. 2022;10(3):288-303.
 35. Reina G. Robotics and AI for precision agriculture. *Robotics*. 2024;13(4):64.
 36. Robertson MJ, Llewellyn RS, Mandel R, Lawes R, Bramley RGV, Swift L, *et al*. Adoption of variable rate fertiliser application in the Australian grains industry: status, issues and prospects. *Precis Agric*. 2012;13(2):181-99.
 37. Roccatallo E, Pagano A, Levorato N, Rumor M. State of the art in IoT standards and protocols for precision agriculture with an approach to semantic interoperability. *Network*. 2025;5(2):14.
 38. Sadhukhan R, Kumar D, Sen S, Sepat S, Ghosh A, Shivay YS, *et al*. Precision nutrient management in zero-till direct-seeded rice influences productivity, profitability, nutrient, and water use efficiency and environmental footprint in Indo-Gangetic plains. *Agriculture*. 2023;13(4):784.
 39. Saki M, Keshavarz R, Franklin D, Abolhasan M, Lipman J, Shariati N. A data-driven review of remote sensing-based data fusion in precision agriculture from foundational to transformer-based techniques. *IEEE Access*. 2025.
 40. Schimmelpfennig D. Crop production costs, profits, and ecosystem stewardship with precision agriculture. *J Agric Appl Econ*. 2018;50(1):81-103.
 41. Schimmelpfennig D. Crop production costs, profits, and ecosystem stewardship with precision agriculture. *J Agric Appl Econ*. 2018;50(1):81-103.
 42. Schultz TW. Institutions and the rising economic value of man. *Am J Agric Econ*. 1968;50(5):1113-22.
 43. Shahi TB, Xu CY, Neupane A, Guo W. Recent advances in crop disease detection using UAV and deep learning techniques. *Remote Sens*. 2023;15(9):2450.
 44. Sharma P, Kumar P, Singh PK, Rana AK. "Precision Agriculture Farming" enhancing farming efficiency through technology integration. In: 2024 1st Int Conf Adv Comput Commun Netw (ICAC2N). 2024. p. 365-70.
 45. Sher M, Minallah N, Frnda J, Khan W. Elevating crop classification performance through CNN-GRU feature fusion. *IEEE Access*. 2024.
 46. Sinha JK. Indian agriculture: a policy-oriented perspective.
 47. Upadhyay A, Chandel NS, Singh KP, Chakraborty SK, Nandede BM, Kumar M, *et al*. Deep learning and computer vision in plant disease detection: a comprehensive review of techniques, models, and trends in precision agriculture. *Artif Intell Rev*. 2025;58(3):92.
 48. Verdouw C, Tekinerdogan B, Beulens A, Wolfert S. Digital twins in smart farming. *Agric Syst*. 2021;189:103046.
 49. Wang J, Wang P, Tian H, Tansey K, Liu J, Quan W. A deep learning framework combining CNN and GRU for improving wheat yield estimates using time series remotely sensed multi-variables. *Comput Electron Agric*. 2023;206:107705.
 50. Wang X, Gan Y, Iio A, Wang Q. Using vegetation indices developed for Sentinel-2 multispectral data to track spatiotemporal changes in leaf area index of temperate deciduous forests. *Geomatics*. 2025;5(1):11.
 51. Wang Z, Xiao S, Wang J, Parab A, Patel S. Reinforcement learning-based agricultural fertilization and irrigation considering N2O emissions and uncertain climate variability. *AgriEngineering*. 2025;7(8):252.
 52. Yousif IA, Sayed AS, Abdelsamie EA, Ahmed AARS, Saeed M, Mohamed ES, *et al*. Efficiency of geostatistical approach for mapping and modeling soil site-specific management zones for sustainable agriculture management in drylands. *Agronomy*. 2024;14(11):2681.
 53. Zhao H, Duan S, Liu J, Sun L, Reymondin L. Evaluation of five deep learning models for crop type mapping using Sentinel-2 time series images with missing information. *Remote Sens*. 2021;13(14):2790.