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Research Article

INTEGRATING DIGITAL TECHNOLOGIES IN AGRICULTURE: LEVERAGING DRONES, SENSORS, AND AI FOR PRECISION CROP MANAGEMENT

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Abstract
Agricultural production increasingly faces climate variability, resource scarcity, environmental degradation, and rising demands for sustainable food systems, creating an urgent need for precise and adaptive crop management. This study examines how integrated drones, wireless field sensors, and artificial intelligence can enhance precision crop management by transforming heterogeneous agricultural data into actionable decision intelligence. A mixed-methods field-based design combined quasi-experimental comparisons, drone-based remote sensing, continuous sensor monitoring, multimodal data integration, artificial intelligence modeling, agronomic measurements, and stakeholder interviews to evaluate technological and operational performance. The findings indicate that integrated digital management improved crop-stress detection, accelerated management responses, increased productivity, and enhanced water, fertilizer, and pesticide-use efficiency compared with conventional practices. Multimodal integration generated stronger predictive performance than isolated technologies by combining spatial, temporal, and environmental information, while human validation remained essential for adapting algorithmic recommendations to field conditions. The study concludes that effective precision agriculture depends not on technology quantity but on integration quality and the capacity to translate data into timely, interpretable, and contextually relevant interventions. The proposed Integrated Agricultural Digital Intelligence Framework establishes a continuous Sense–Integrate–Analyze–Decide–Act–Learn cycle, providing a foundation for adaptive, resource-efficient, and sustainable crop management across diverse agricultural contexts worldwide.

Keywords: Artificial Intelligence, Digital Agriculture, Drones, Precision Crop Management, Wireless Sensors

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INTRODUCTION

Global agriculture faces increasing pressure to produce sufficient and nutritious food under conditions of population growth, climate variability, land degradation, water scarcity, rising input costs, and ecological constraints (Byrareddy et al., 2026). Conventional crop-management practices often rely on generalized recommendations applied uniformly across fields despite substantial spatial and temporal variations in soil properties, crop conditions, moisture availability, pest pressure, and nutrient requirements. Such variability can reduce resource-use efficiency and contribute to unnecessary applications of water, fertilizers, and pesticides (Xia et al., 2025). Sustainable agricultural transformation therefore requires management systems capable of recognizing field-level heterogeneity and responding to crop needs with greater precision, timeliness, and adaptability.

Precision agriculture has emerged as a data-driven approach for managing agricultural variability through site-specific observation, analysis, prediction, and intervention (Rahimzad et al., 2026). Advances in unmanned aerial vehicles or drones, Internet of Things sensors, remote sensing, cloud computing, geographic information systems, machine learning, and artificial intelligence have substantially expanded the capacity to monitor agricultural environments. These technologies can generate high-resolution information on crop health, soil moisture, temperature, nutrient conditions, vegetation indices, disease symptoms, and environmental stress (Moussaid et al., 2026). Their growing availability creates opportunities to shift crop management from reactive and experience-dependent practices toward predictive and evidence-informed decision-making.

Drones, sensors, and artificial intelligence perform distinct but potentially complementary functions within precision crop management (Rehman et al., 2024). Drones provide rapid aerial observation and high-resolution spatial imagery, field sensors generate continuous localized measurements of environmental and soil conditions, while AI algorithms transform large and heterogeneous datasets into classifications, predictions, recommendations, and automated decisions. Their integration can theoretically create a continuous cycle of Sense Analyze Decide Act Learn, allowing agricultural management systems to detect variability, interpret changing conditions, recommend interventions, evaluate outcomes, and improve subsequent decisions.

The principal problem is that agricultural digitalization often occurs through fragmented technological adoption rather than through integrated decision-support ecosystems (Rai et al., 2026). Farmers may use drones for aerial mapping, sensors for soil monitoring, weather stations for environmental observation, or software platforms for farm management without effective interoperability among these technologies. Fragmented data streams can create information abundance without necessarily improving decision quality (Subeesh & Chauhan, 2026). The practical value of digital agriculture therefore depends less on the presence of individual technologies than on their capacity to exchange data and generate coordinated, actionable recommendations.

Data integration presents a significant technical challenge because agricultural information is heterogeneous in format, scale, frequency, and spatial resolution (Talaeizadeh et al., 2025). Drone imagery may capture detailed spatial variation at selected intervals, while field sensors continuously generate point-based measurements. Satellite data, weather forecasts, historical yield records, and farm-management information introduce additional layers of complexity. AI models require reliable, representative, and sufficiently integrated datasets to generate accurate predictions (Bitakou et al., 2026). Poor sensor calibration, missing observations, inconsistent data standards, limited connectivity, and model bias can weaken the reliability of precision-management recommendations.

Socioeconomic and institutional barriers further complicate digital agricultural transformation (Morgan et al., 2026). High initial investment costs, limited digital literacy, inadequate rural connectivity, insufficient technical support, data-ownership concerns, cybersecurity risks, and uncertainty regarding economic returns may restrict adoption, particularly among smallholder farmers. Technological sophistication does not automatically produce agricultural benefits when systems are unaffordable, difficult to operate, or poorly aligned with local farming conditions (Mamabolo et al., 2025). Precision agriculture must therefore be evaluated not only according to technological performance but also through usability, accessibility, economic feasibility, scalability, farmer trust, and environmental outcomes.

This study aims to examine how the integration of drones, field sensors, and artificial intelligence can improve precision crop management through coordinated agricultural monitoring, predictive analysis, and site-specific decision-making (Bhardwaj et al., 2026). The research focuses on the complementary roles of these technologies rather than evaluating each tool independently. Drones are examined as spatial observation systems, sensors as continuous field-monitoring mechanisms, and AI as an analytical layer capable of transforming multimodal agricultural data into actionable management intelligence.

The study seeks to evaluate the contribution of integrated digital technologies to critical crop-management decisions involving irrigation, fertilization, pest and disease detection, crop-stress monitoring, and yield prediction (Nath et al., 2026). Particular attention is directed toward whether integrated systems improve the accuracy and timeliness of interventions compared with conventional or technologically fragmented management approaches. Resource-use efficiency, crop productivity, early-risk detection, and environmental performance constitute important outcome dimensions for assessing the practical effectiveness of digital integration.

The research also aims to identify the technological, socioeconomic, and institutional conditions that determine successful implementation. Factors including interoperability, data quality, connectivity, AI model reliability, farmer digital competence, affordability, technical support, farm size, and local environmental conditions are examined as potential enablers or constraints (Khoshnodifar et al., 2025). This broader objective recognizes that the effectiveness of precision agriculture depends on the interaction between technological capability and the agricultural contexts within which technologies are implemented.

Existing research has generated substantial evidence concerning individual digital technologies in agriculture (Eze & Fiume, 2026). Drone-based studies have demonstrated applications in crop mapping, vegetation monitoring, disease detection, and spraying, while sensor research has examined soil moisture, temperature, nutrient status, and microclimatic conditions. Artificial intelligence studies have developed models for crop classification, disease recognition, yield prediction, irrigation scheduling, and decision support. Much of this literature evaluates technologies separately, creating extensive knowledge about technological performance but less understanding of how multiple technologies operate as an integrated crop-management system.

A second research gap concerns the transition from monitoring accuracy to actionable agricultural decision-making. Many studies demonstrate that drones can produce accurate imagery or that machine-learning models can achieve high predictive performance under experimental conditions (R. Kumar et al., 2026). Fewer studies systematically examine whether these technological outputs lead to better management decisions, reduced input consumption, improved productivity, or measurable environmental benefits under operational farming conditions. High algorithmic accuracy does not necessarily translate into agronomic value if recommendations are delayed, difficult to interpret, economically impractical, or disconnected from actual farm-management processes.

A third gap concerns the limited integration of technical performance with adoption, equity, and sustainability considerations. Research frequently emphasizes accuracy, automation, and technological efficiency while giving less attention to affordability, interoperability, farmer capability, data governance, explainability, and smallholder accessibility (Gueboudji, 2026). Such omissions may produce technologically impressive systems with limited real-world adoption. A comprehensive understanding of digital agriculture therefore requires simultaneous examination of technical integration, decision quality, agronomic outcomes, socioeconomic feasibility, and environmental sustainability.

The principal novelty of this study lies in conceptualizing precision crop management through an Integrated Agricultural Digital Intelligence Framework structured around the cycle Sense - Integrate - Analyze - Decide - Act - Learn. Drones and field sensors function as complementary sensing mechanisms, data integration creates a unified representation of field conditions, AI transforms multimodal information into predictions and recommendations, management decisions translate intelligence into targeted interventions, and outcome data provide feedback for continuous system improvement (Yang & Tang, 2026). This framework moves beyond technology-centered precision agriculture toward an adaptive agricultural intelligence ecosystem.

A second element of novelty concerns the integration of technological performance, agronomic value, and implementation feasibility within a single analytical perspective. The study does not assume that more advanced technology necessarily produces better farming outcomes. An AI model with high predictive accuracy may have limited practical value if farmers cannot interpret its recommendations, if sensor maintenance is prohibitively expensive, or if rural connectivity prevents real-time operation (Mehrotra et al., 2026). The research therefore evaluates digital integration according to whether it produces actionable intelligence, defined as information that is accurate, timely, interpretable, contextually relevant, economically feasible, and capable of informing concrete agricultural decisions.

The study is justified by the urgent need to reconcile agricultural productivity with environmental sustainability and resource efficiency (Volpato et al., 2024). Climate uncertainty, water scarcity, soil degradation, and rising production costs require more adaptive forms of crop management, yet digitalization should not be treated as an automatic solution to these structural challenges. Integrated drones, sensors, and AI can create significant value when technological capabilities are aligned with agronomic knowledge, farmer needs, and local conditions. Understanding this alignment can provide a stronger foundation for developing precision agriculture systems that move beyond data collection toward decision intelligence, beyond automation toward adaptive management, and beyond technological innovation toward measurable agricultural and environmental value.

RESEARCH METHOD

Research Design

This study employed a mixed-methods field-based research design to investigate the integration of drones, field sensors, and artificial intelligence for precision crop management. The quantitative component used a quasi-experimental approach to compare digitally integrated precision management with conventional or partially digitalized farming practices across selected agricultural plots (Cheikhrouhou et al., 2026). The qualitative component examined farmers' and agricultural practitioners' experiences regarding usability, decision relevance, technological barriers, and implementation feasibility. This combination allowed the study to evaluate technological performance while accounting for the agronomic and human contexts in which digital technologies were implemented.

The research design was guided by the Integrated Agricultural Digital Intelligence Framework, structured around the operational cycle of Sense - Integrate - Analyze - Decide - Act - Learn. Drones and field sensors constituted the sensing layer, while data-fusion mechanisms integrated spatial, temporal, environmental, and crop-related observations. Artificial intelligence functioned as the analytical layer for detecting patterns, predicting crop conditions, and generating management recommendations. Site-specific interventions represented the action stage, while subsequent crop and environmental observations provided feedback for evaluating outcomes and refining future decisions.

The study focused on four major precision-management domains: irrigation optimization, nutrient management, crop-stress detection, and pest or disease monitoring. Agricultural productivity and resource-use efficiency were treated as primary outcome dimensions, while decision timeliness, predictive accuracy, environmental performance, and user acceptance were examined as complementary indicators (El Hachimi et al., 2025). The design did not assume that technological sophistication automatically improved agricultural performance. Digital integration was evaluated according to its ability to produce actionable, agronomically relevant, and operationally feasible decisions.

Research Target/Subject

The study population consisted of agricultural production units and farmers engaged in crop cultivation within selected agricultural regions where digital monitoring technologies could be operationally deployed. Eligible farms were required to have active crop production, sufficient field accessibility for drone operations, willingness to install sensor systems, and availability of basic historical or current farm-management records. Farms representing variation in field size, crop-management intensity, technological readiness, and environmental conditions were considered to improve the ecological relevance of the study.

A multistage purposive sampling procedure was used to select agricultural sites and experimental plots. Selected fields were categorized into digitally integrated precision-management plots and comparison plots managed through conventional or partially digitalized practices (Manimozhian & Chandel, 2026). Matching criteria included crop type, field size, soil characteristics, planting period, irrigation conditions, and baseline management practices. This procedure was intended to reduce systematic differences between comparison groups while recognizing that complete randomization was not feasible under operational farming conditions.

Farmers, farm managers, agricultural extension personnel, and technical operators directly involved in the selected sites constituted the human-participant sample for the implementation component. Participants were selected according to their involvement in crop-management decisions, experience with agricultural technologies, and knowledge of local production conditions. Variation in age, farming experience, digital competence, farm scale, and prior exposure to precision-agriculture technologies was considered to capture different perspectives on technological adoption and usability.

Sample adequacy for quantitative analysis was determined through an a priori power analysis based on the expected effect sizes, number of comparison groups, repeated observations, and multivariate analyses planned for the study. Qualitative sampling continued until sufficient thematic depth was achieved across key implementation categories. The sampling strategy emphasized analytical representativeness rather than assuming that findings from technologically enabled demonstration sites could automatically be generalized to all agricultural systems.

Research Procedure

The research began with site selection, baseline assessment, ethical and operational approval, participant recruitment, field mapping, and technological preparation. Baseline data were collected on soil conditions, crop characteristics, historical management practices, irrigation patterns, input use, and previous productivity where reliable records were available (Yan et al., 2025). Drone flight plans and sensor-placement strategies were developed according to field characteristics, crop type, regulatory requirements, and data-resolution needs.

The sensing phase involved synchronized collection of aerial, field-sensor, weather, and crop-management data. Drone flights were conducted at predefined crop-development stages and when field conditions permitted safe and consistent data acquisition. Sensor networks continuously recorded environmental and soil conditions at established intervals. Quality-control procedures identified missing observations, implausible measurements, sensor drift, image-quality problems, and temporal inconsistencies before data integration.

The integration phase combined heterogeneous datasets through temporal alignment, spatial referencing, data cleaning, normalization, and feature extraction. Drone-derived spatial information was linked with sensor observations, weather conditions, crop-development indicators, and management records. Missing-data procedures were selected according to the pattern and extent of missingness, while anomalous values were reviewed rather than automatically removed. Data provenance was documented to maintain transparency regarding the origin and transformation of analytical inputs.

The analysis phase applied machine-learning procedures to identify patterns and generate predictions relevant to crop management. Data were separated into training, validation, and testing subsets while avoiding inappropriate information leakage across spatially or temporally related observations. Cross-validation was used where appropriate to evaluate model stability. Model performance was compared against baseline approaches to determine whether integrated multimodal data provided meaningful predictive improvement over single-source or conventional methods.

The decision phase translated validated analytical outputs into agronomically interpretable recommendations. AI-generated predictions were reviewed alongside field observations and expert knowledge before management actions were implemented. This human-in-the-loop procedure was designed to reduce the risk of inappropriate interventions resulting from sensor errors, model uncertainty, or contextually incomplete data. Recommendations were recorded together with the reasoning, confidence level, and resulting management decision.

The action phase involved site-specific crop-management interventions based on validated recommendations. Irrigation, nutrient application, field inspection, or pest-management responses were adjusted according to identified spatial and temporal requirements where operationally feasible (Boulealam et al., 2026). Comparison plots continued under conventional or existing management procedures. All interventions, input quantities, timing, labor requirements, and operational deviations were systematically documented.

The learning phase evaluated the outcomes of interventions through subsequent drone observations, sensor measurements, field assessments, and production data. Differences in crop health, yield, water consumption, input use, intervention timing, and resource-use efficiency were examined between integrated precision-management and comparison conditions. Feedback from observed outcomes was incorporated into subsequent analytical cycles, enabling refinement of thresholds, model parameters, and management recommendations.

Quantitative analysis included descriptive statistics, group comparisons, repeated-measures procedures where appropriate, regression analysis, and multivariate modeling. Treatment effects were estimated while controlling for relevant baseline differences and environmental covariates. Effect sizes and confidence intervals were reported alongside statistical significance. Sensitivity analyses were conducted where possible to examine whether results remained stable under alternative analytical specifications.

Qualitative data from interviews and implementation observations were analyzed thematically to identify patterns related to usability, trust, perceived benefits, implementation barriers, affordability, and compatibility with farming practices. Quantitative and qualitative findings were integrated to distinguish technological effectiveness from practical adoptability. A system demonstrating high predictive accuracy but low interpretability, excessive cost, or poor operational compatibility was not automatically classified as successful.

Final interpretation followed the Integrated Agricultural Digital Intelligence Framework, examining how effectively the system completed the cycle of Sense - Integrate - Analyze - Decide - Act - Learn. The evaluation emphasized that the value of agricultural digitalization lies not in maximizing the number of technologies deployed but in improving the quality, timeliness, precision, and sustainability of agricultural decisions. The methodological framework therefore assessed whether integrated drones, sensors, and AI could transform heterogeneous field data into actionable intelligence that generated measurable agronomic value under real farming conditions.

Instruments, and Data Collection Techniques

Drone-based remote-sensing systems were used to collect high-resolution aerial imagery across experimental fields at predefined intervals and critical crop-development stages. Unmanned aerial vehicles equipped with RGB and multispectral cameras captured information related to canopy development, vegetation condition, spatial variability, and visible signs of crop stress. Vegetation indices, including the Normalized Difference Vegetation Index where sensor specifications permitted, were derived from aerial imagery to support the identification of crop-health patterns and anomalous field zones.

Wireless field sensors were installed to continuously measure selected environmental and soil variables, including soil moisture, soil temperature, air temperature, relative humidity, and other agronomically relevant indicators supported by the available sensor configuration (Apollon et al., 2026). Sensor placement followed field variability and experimental requirements rather than uniform convenience sampling. Calibration procedures were conducted before deployment, and periodic validation against reference measurements was used to reduce measurement drift and identify malfunctioning devices.

The artificial intelligence component consisted of machine-learning models designed to integrate drone imagery, sensor measurements, weather information, crop-development data, and selected management records. Models were developed for crop-stress classification, irrigation requirements, disease-risk detection, and yield-related prediction where sufficient data were available. Model performance was evaluated using appropriate metrics such as accuracy, precision, recall, F1-score, root mean square error, mean absolute error, and coefficient of determination according to the nature of each analytical task.

A digital decision-support interface was used to translate analytical outputs into interpretable management recommendations. Recommendations included irrigation timing, identification of stress zones, priority areas for field inspection, and targeted management responses (Storm et al., 2024). The system preserved uncertainty estimates where possible rather than presenting every algorithmic output as a definitive recommendation. Agronomic validation by researchers, farmers, or agricultural specialists was incorporated before high-consequence field interventions.

Agronomic measurement instruments were used to evaluate crop growth, yield, water use, fertilizer application, pesticide use, and selected indicators of resource-use efficiency. Standardized field observation sheets documented crop conditions, management interventions, and relevant environmental events throughout the study period. Historical production records and farm-management logs were used where sufficiently reliable to establish contextual baselines.

A structured questionnaire and semi-structured interview protocol were used to evaluate user experiences with the integrated digital system. The instruments assessed perceived usefulness, ease of use, trust in AI-generated recommendations, interpretability, compatibility with existing farming practices, perceived economic feasibility, technical barriers, and intention to continue using the technology. Expert review and pilot testing were conducted to improve content validity, clarity, and contextual appropriateness.

Data Analysis Technique

Quantitative data were analyzed using descriptive statistics, group comparisons, repeated-measures analysis, regression, and multivariate techniques to evaluate differences between integrated precision-management and comparison plots. Machine-learning models were assessed using accuracy, precision, recall, F1-score, RMSE, MAE, and R^2 as appropriate, while effect sizes, 95% confidence intervals, and a significance level of $p < 0.05$ were used to support statistical interpretation.

Qualitative data from interviews and field observations were analyzed thematically to identify patterns related to usability, trust, perceived benefits, barriers, and technology adoption. Quantitative and qualitative findings were then integrated to assess whether the combined use of drones, sensors, and AI produced accurate, actionable, and operationally feasible decisions that improved productivity, resource-use efficiency, and sustainable crop management.

RESULTS AND DISCUSSION

The integrated precision crop management system generated multimodal data from drone imagery, wireless field sensors, weather observations, farm-management records, and direct agronomic measurements throughout the cultivation period. Descriptive analysis showed that plots managed through the integrated drone–sensor–AI system achieved an average crop yield of 6.84 t/ha compared with 5.92 t/ha in conventionally managed comparison plots. Average irrigation water consumption declined from 4,620 m^3/ha under conventional management to 3,710 m^3/ha under integrated precision management. Fertilizer application decreased from 286 kg/ha to 247 kg/ha, while pesticide application frequency declined from an average of 4.8 to 3.5 applications per production cycle. These patterns indicate simultaneous improvements in production and resource-use efficiency rather than productivity gains achieved through increased agricultural inputs.

Table 1. Comparative Performance of Integrated Digital Precision Management and Conventional Crop Management

Indicator	Integrated Drone Sensor AI Management	Conventional Management	Relative Change
Crop Yield (t/ha)	6.84	5.92	+15.54%
Irrigation Water Use (m^3/ha)	3,710	4,620	−19.70%
Fertilizer Application (kg/ha)	247	286	−13.64%
Pesticide Applications (times/cycle)	3.5	4.8	−27.08%
Water-Use Efficiency (kg/m^3)	1.84	1.28	+43.75%
Crop-Stress Detection Accuracy (%)	91.6	72.8	+18.8 percentage points
Average Stress Detection Lead Time (days)	4.7 earlier	Reference	—
Decision Response Time (hours)	9.6	27.4	−64.96%

Secondary analysis of operational records indicated that the integrated system detected crop-stress conditions an average of 4.7 days before symptoms became consistently identifiable through conventional visual field inspection. Drone-derived vegetation indicators identified spatial anomalies across crop canopies, while soil-moisture and microclimatic sensors provided continuous temporal evidence regarding field conditions. AI-based integration improved the prioritization of areas requiring inspection and intervention. The combined information reduced dependence on uniform field-level treatment by identifying specific zones requiring irrigation, nutrient adjustment, or pest and disease assessment.

The observed increase in crop yield was associated with greater precision in the timing and spatial targeting of agricultural interventions. Conventional management frequently applied irrigation and inputs according to generalized schedules or whole-field assumptions, while the integrated system responded to localized differences in soil moisture, vegetation condition, environmental stress, and predicted crop requirements (Elhoseny et al., 2026). This site-specific approach reduced the likelihood of both under-treatment and unnecessary input application. Yield improvements therefore appeared to result from better synchronization between crop needs and management responses rather than from increased resource consumption.

The reduction in water, fertilizer, and pesticide use reflected the capacity of integrated digital monitoring to distinguish areas requiring intervention from those where additional inputs were unnecessary. Sensor measurements provided continuous information on soil and environmental conditions, while drone imagery revealed spatial patterns that point-based measurements alone could not adequately capture (Morchid et al., 2026). AI-based analysis combined these complementary data streams into management recommendations. The findings demonstrate that technological integration generated greater value than isolated monitoring because spatial, temporal, and predictive information could be interpreted within a unified decision process.

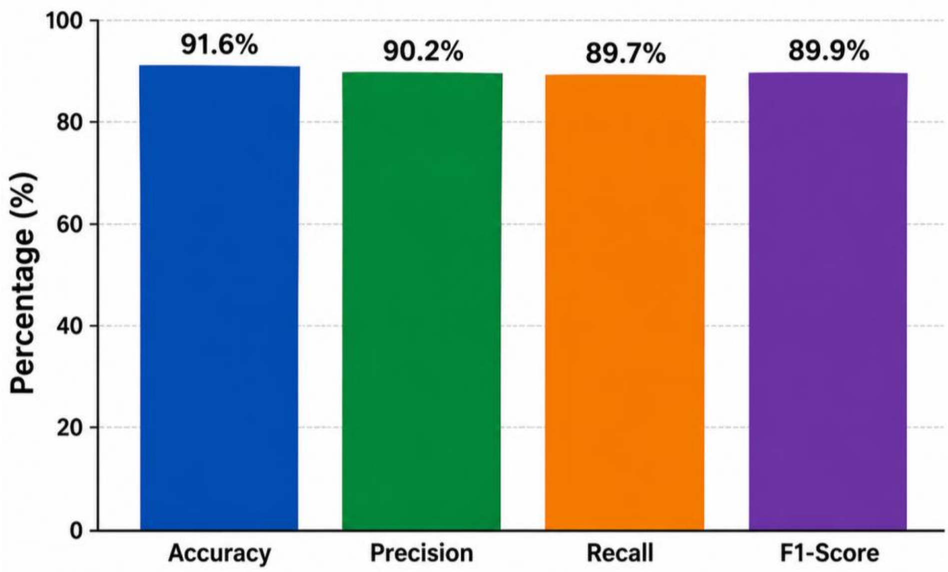

Figure 1. AI Supported Crop Stress Detection Performance

Drone-based crop monitoring achieved high spatial sensitivity in detecting heterogeneous crop conditions. Multispectral and RGB imagery identified canopy irregularities, vegetation stress, and potential disease-affected zones before widespread visible symptoms developed. AI-supported classification achieved an overall crop-stress detection accuracy of 91.6%, with precision of 90.2%, recall of 89.7%, and an F1-score of 89.9%. Sensor-enhanced models performed more consistently across variable environmental conditions than image-only models, particularly when visual crop symptoms were ambiguous.

Wireless sensor data demonstrated substantial within-field and temporal variability in soil-moisture conditions. Some areas reached critical moisture thresholds several hours or days earlier than others despite receiving similar irrigation under conventional scheduling. The integrated system used these differences to generate zone-specific irrigation recommendations. Decision logs showed that approximately 63% of irrigation events in digitally managed plots were modified in timing, duration, or spatial allocation based on real-time or near-real-time data, illustrating the practical influence of sensor information on operational decisions.

Inferential analysis indicated that digitally integrated precision management had a statistically significant positive effect on crop yield after controlling for baseline soil characteristics, initial crop conditions, and selected environmental covariates ($\beta = .37$, $p < .001$). Integrated management was also significantly associated with lower irrigation water consumption ($\beta = -.42$, $p < .001$), reduced fertilizer use ($\beta = -.28$, $p = .004$), and fewer pesticide applications ($\beta = -.25$, $p = .009$). Effect-size estimates suggested that the strongest practical improvement occurred in water-use efficiency, followed by decision-response time and crop productivity.

Repeated-measures analysis showed a significant interaction between management approach and crop-development stage for vegetation-health indicators ($p < .001$), suggesting that differences between integrated and conventional management became more pronounced during periods of greater environmental stress. Mixed-effects modeling, with repeated sensor and imagery observations nested within experimental plots, confirmed that the observed effects remained statistically meaningful after accounting for within-plot measurement dependence. This analytical structure prevented the large volume of sensor readings and drone observations from being incorrectly treated as independent experimental units.

Correlation analysis revealed a strong positive relationship between the quality of integrated data and AI prediction accuracy ($r = .64$, $p < .001$). Prediction accuracy was positively associated with decision timeliness ($r = .52$, $p < .001$) and crop yield performance ($r = .41$, $p < .001$). Decision timeliness was also positively related to water-use efficiency ($r = .48$, $p < .001$), suggesting that the practical value of predictive analytics depended partly on whether recommendations could be translated rapidly into field-level interventions.

Model-comparison analysis demonstrated that multimodal integration outperformed single-source analytical approaches. Drone-only models achieved 84.3% accuracy in crop-stress classification, while sensor-only models achieved 81.7%. The integrated drone–sensor–weather model reached 91.6% accuracy. The improvement indicates that different technologies captured complementary dimensions of agricultural conditions rather than merely duplicating the same information. Drone imagery provided spatial coverage, sensors captured continuous temporal dynamics, weather data contextualized environmental variation, and AI created an analytical mechanism for combining these information sources.

Figure 2. Delayed Water Stress Detection

A representative field case demonstrated the operational value of integrated digital monitoring during an emerging water-stress event. Drone imagery identified a declining vegetation index in a specific section of the field that appeared visually normal during routine inspection. Soil-moisture sensors located within and near the affected zone simultaneously recorded moisture levels approaching a predefined stress threshold (Majdalawieh et al., 2025). The AI model classified the area as having a high probability of developing moderate water stress within the following 48 hours and recommended targeted irrigation rather than whole-field watering.

Targeted intervention was implemented after agronomic verification of the recommendation. Follow-up sensor measurements showed recovery in soil-moisture conditions, while subsequent drone observations indicated stabilization of vegetation-health indicators (Hashem et al., 2026). The intervention used approximately 31% less water than the estimated requirement for a conventional whole-field irrigation event. No substantial yield reduction was recorded in the affected zone at harvest. The case illustrates how the integrated system converted early detection into a targeted management response before stress developed into measurable crop damage.

The case-study evidence explains why integration produced greater operational value than independent technological use. Drone imagery alone could identify an abnormal spatial pattern but could not fully explain its underlying cause. Soil-moisture sensors provided evidence of water deficiency but represented localized measurements that could not independently determine the full spatial extent of the problem. AI-supported data fusion connected these complementary observations and generated a probabilistic interpretation that could be evaluated by farmers and agronomic personnel before intervention.

Human validation remained important despite the high predictive performance of the system. Farmers and agricultural specialists occasionally modified AI-generated recommendations because of irrigation infrastructure limitations, weather forecasts, crop-development considerations, or local field knowledge not fully represented in the model. Approximately 14.2% of automated recommendations were adjusted before implementation, while 3.8% were rejected after field verification. These findings indicate that effective precision agriculture operated as a human–AI decision system rather than as fully autonomous technological control.

The overall findings indicate that integrating drones, field sensors, weather information, and AI generated greater agronomic value than relying on isolated digital technologies or conventional crop-management practices. The integrated system improved crop-stress detection, shortened decision-response time, increased yield, and reduced water, fertilizer, and pesticide use (S. Kumar et al., 2024). The strongest benefits emerged when complementary data sources were transformed into timely and site-specific recommendations that could be validated and implemented within actual farming operations. Digitalization therefore created value through decision quality rather than through technology deployment alone.

The results provide preliminary empirical support for the Integrated Agricultural Digital Intelligence Framework represented by the cycle Sense - Integrate - Analyze - Decide - Act → Learn. Sensing technologies generated spatial and temporal evidence, data integration created a more complete representation of field conditions, AI transformed heterogeneous observations into predictive intelligence, human-supported decisions translated predictions into targeted actions, and post-intervention measurements created feedback for subsequent management cycles. The findings suggest that the future of precision crop management lies not simply in deploying more drones, sensors, or sophisticated algorithms, but in building integrated and adaptive systems capable of converting agricultural data into reliable, interpretable, timely, and resource-efficient field decisions.

The findings demonstrate that integrating drones, wireless field sensors, weather information, and artificial intelligence can improve precision crop management by transforming heterogeneous agricultural data into timely and site-specific decision support. Digitally integrated management was associated with higher crop productivity, lower irrigation water consumption, more efficient fertilizer use, fewer pesticide applications, and faster detection of crop stress than conventional management. These improvements indicate that digital agriculture creates its greatest value when technologies operate as interconnected components of a decision system rather than as isolated monitoring tools.

Multimodal data integration produced stronger analytical performance than single-source approaches. Drone imagery provided detailed spatial information on crop variability, while field sensors captured continuous temporal changes in soil and environmental conditions. Weather information added contextual evidence, and AI models integrated these complementary data streams to identify patterns that individual technologies could not fully interpret independently (Vahidi et al., 2025). The superior performance of integrated models suggests that the principal technological advantage lies in information complementarity rather than simply increasing the volume of agricultural data.

Decision timeliness emerged as an important mechanism connecting predictive intelligence with agronomic outcomes. Earlier identification of crop stress enabled farmers to intervene before visible symptoms developed into substantial physiological or productivity losses. Site-specific recommendations also reduced unnecessary whole-field treatments by directing irrigation, field inspection, and other interventions toward areas with demonstrated or predicted needs (Rayamajhi et al., 2024). Precision management therefore improved not only the accuracy of agricultural observation but also the timing and spatial specificity of management responses.

Human validation remained essential despite strong AI performance. Farmers and agricultural specialists modified or rejected some algorithmic recommendations when local knowledge, infrastructure constraints, weather expectations, or crop-development considerations were not adequately represented in the model. This finding indicates that effective precision agriculture should not be conceptualized as the replacement of farmers by autonomous algorithms. The strongest operational model was a human–AI decision architecture in which computational intelligence augmented rather than displaced agronomic judgment.

The findings are consistent with previous research demonstrating the value of drones for high-resolution crop monitoring and early stress detection. Drone-based multispectral and RGB imagery has been widely applied to vegetation assessment, crop mapping, disease identification, and yield estimation. The present study extends this technological perspective by showing that aerial information becomes more actionable when combined with ground-based sensor measurements and contextual environmental data. Spatial observation alone may identify where an abnormality occurs without fully explaining why it occurs or how rapidly conditions are changing.

The results also correspond with studies reporting that Internet of Things sensors can improve irrigation scheduling and environmental monitoring through continuous field-level measurements. Sensor systems provide valuable temporal information but often represent localized conditions around specific measurement points (Xu et al., 2026). The present findings demonstrate that integrating point-based sensor observations with drone-derived spatial information can reduce this limitation. The combination creates a more comprehensive representation of field heterogeneity than either sensing approach can provide independently.

Research on artificial intelligence in agriculture has frequently emphasized predictive accuracy in disease classification, crop recognition, irrigation prediction, and yield forecasting. The present study differs by treating algorithmic accuracy as an intermediate rather than final measure of technological success. A model can achieve high classification performance without producing meaningful agronomic benefits if recommendations are delayed, difficult to interpret, economically impractical, or disconnected from field operations. The findings therefore shift evaluation from prediction accuracy alone toward actionable decision quality.

The study also extends existing precision-agriculture literature by emphasizing closed-loop learning rather than one-directional technological monitoring. Many digital agriculture systems follow a linear process in which data are collected, analyzed, and presented to users. The proposed framework adds action and feedback as essential components. Management outcomes become new evidence for subsequent analytical cycles, creating the possibility of adaptive improvement over time. This distinction moves precision agriculture conceptually from static decision support toward continuously learning agricultural intelligence.

The findings signify that agricultural digitalization should not be measured by the number or sophistication of technologies deployed. Farms equipped with drones, sensors, and AI platforms are not necessarily practicing effective precision agriculture if those technologies remain disconnected or produce information that does not influence management decisions (Biswas et al., 2026). Technological adoption and decision transformation are fundamentally different outcomes. Digital agriculture becomes meaningful when data improve what farmers know, when they know it, and how effectively they can respond.

The superiority of multimodal integration signifies that agricultural complexity cannot be adequately represented through a single data source. Crop performance emerges from interactions among soil conditions, water availability, weather, biological processes, management practices, and spatial variability. Each sensing technology captures only part of this system. Integrated agricultural intelligence becomes more powerful because it combines multiple perspectives on the same underlying crop environment.

The importance of early detection signifies a transition from reactive toward predictive crop management. Conventional practices often respond after stress, disease, or resource deficiency becomes visually apparent. Digital sensing and predictive analytics create opportunities to identify risk before substantial damage occurs. This temporal advantage can fundamentally change management logic from treating observable problems toward anticipating emerging conditions and intervening at earlier, potentially less costly stages.

The continued importance of farmer judgment signifies that AI should be understood as an augmentation technology rather than an autonomous authority. Agricultural decisions are embedded in contexts involving weather uncertainty, market conditions, infrastructure, labor availability, farmer experience, and local ecological knowledge. Not all relevant information can be captured in a dataset or model. Effective digital agriculture therefore depends on combining computational scalability with contextual human intelligence.

The principal theoretical implication lies in the Integrated Agricultural Digital Intelligence Framework, organized through the cycle Sense - Integrate - Analyze → Decide → Act - Learn. This framework expands conventional precision-agriculture models by positioning data integration, actionable decision-making, intervention, and feedback as equally important components of digital transformation. The value of sensing technology is conditional on whether data can move effectively through the entire cycle and generate measurable agronomic outcomes.

The practical implication concerns technology investment and farm-management strategy. Agricultural producers should avoid adopting digital tools solely because individual technologies demonstrate technical sophistication. Investment decisions should prioritize interoperability, data quality, decision relevance, usability, and compatibility with existing farming operations. A less sophisticated but well-integrated system may generate greater practical value than multiple advanced technologies operating independently.

The environmental implication concerns resource-use efficiency. Site-specific irrigation, nutrient management, and targeted pest interventions can reduce unnecessary resource consumption while maintaining or improving productivity. Such improvements are increasingly important under conditions of water scarcity, soil degradation, rising input costs, and environmental pressure. Precision agriculture can therefore contribute to sustainability when digital intelligence is explicitly connected to resource optimization rather than used primarily to maximize production.

The policy implication concerns equitable digital agricultural transformation. High investment costs, weak rural connectivity, limited technical support, insufficient digital literacy, and fragmented data infrastructure may prevent smallholder farmers from accessing integrated precision technologies. Policies focused only on technological innovation risk widening the digital divide between capital-intensive and resource-constrained agricultural systems. Public investment, cooperative technology models, extension services, shared drone facilities, affordable sensor networks, and digital capacity development are necessary to broaden access.

The observed productivity improvements likely occurred because integrated digital management reduced mismatches between crop requirements and management interventions. Conventional whole-field practices often assume relatively uniform conditions despite substantial spatial variation. Integrated sensing identified heterogeneous crop and soil conditions, allowing interventions to be adjusted according to localized requirements. Better alignment between crop needs and management timing likely contributed to improved productivity without proportional increases in input use.

The reduction in irrigation water use can be explained by the complementary relationship between soil-moisture sensing and spatial crop monitoring. Sensors indicated when moisture conditions approached critical thresholds, while drone imagery helped determine where crop responses suggested emerging stress. Combining these data reduced unnecessary irrigation based solely on fixed schedules. Water could therefore be applied more selectively according to actual or predicted field conditions.

The higher predictive performance of multimodal AI models likely resulted from information complementarity. Drone imagery captured visible and spectral crop characteristics, sensors measured environmental and soil dynamics, and weather data provided contextual information affecting crop responses. Individual data sources contained partial representations of agricultural conditions. Data fusion reduced informational blind spots and enabled AI models to distinguish among patterns that might appear similar when evaluated through only one source.

The effectiveness of human–AI collaboration occurred because farmers contributed contextual knowledge unavailable to computational models. Irrigation infrastructure limitations, equipment availability, short-term weather expectations, labor constraints, and local field history influenced whether recommendations were practically appropriate. AI provided analytical capacity across large and complex datasets, while human judgment evaluated recommendations against operational reality. Their complementary strengths created a more robust decision process than either fully manual or fully automated management.

Future research should employ multi-season and multi-location field trials to determine whether the observed benefits remain stable across crop types, soil conditions, climatic environments, and farming systems. Short-term technological performance may not accurately represent long-term agronomic effectiveness because sensor reliability, model drift, seasonal variability, and changing management conditions can influence outcomes. Longitudinal evidence is necessary before broad claims regarding scalability can be established.

Future studies should investigate whether integrated precision agriculture remains economically viable after accounting for total ownership costs. Drone acquisition or service fees, sensor installation and maintenance, connectivity, software subscriptions, AI infrastructure, technical expertise, and training should be compared with productivity gains and input savings. Economic evaluation should distinguish technical feasibility from financial sustainability, particularly for smallholder and resource-constrained farms.

Future research should strengthen AI explainability, uncertainty quantification, and data governance. Farmers need to understand not only what an algorithm recommends but also why a recommendation was generated, how confident the system is, and which data influenced the prediction. Transparent decision support can improve trust while reducing inappropriate reliance on automated outputs. Data ownership, cybersecurity, privacy, interoperability, and control over agricultural information also require systematic attention as farming becomes increasingly data-intensive.

Future scholarship should ultimately shift from asking whether individual technologies such as drones, sensors, or AI can improve agriculture toward examining how integrated digital intelligence can improve agricultural decisions under real-world uncertainty. The next generation of precision agriculture should move beyond monitoring toward prediction, prediction toward decision, decision toward targeted action, and action toward continuous learning. Such a transition can transform digital agriculture from a collection of technological tools into an adaptive human–AI agricultural intelligence ecosystem capable of balancing productivity, resource efficiency, economic feasibility, and environmental sustainability.

CONCLUSION

The most significant finding of this study is that the effectiveness of digital technologies in precision crop management depends less on the independent performance of drones, sensors, or artificial intelligence than on their capacity to operate as an integrated decision-making ecosystem. The combination of high-resolution spatial observations from drones, continuous temporal measurements from field sensors, contextual environmental information, and AI-supported predictive analytics improved the detection of crop stress, accelerated management responses, enhanced resource-use efficiency, and supported higher crop productivity. Multimodal integration generated greater analytical and agronomic value than isolated technological applications because complementary data reduced informational gaps and enabled more precise interpretation of field variability. Human validation remained essential for translating algorithmic recommendations into contextually appropriate interventions, demonstrating that effective precision agriculture is best understood as a human–AI collaborative system rather than a fully autonomous technological process.

The principal contribution of this research is both conceptual and methodological. Conceptually, the study proposes the Integrated Agricultural Digital Intelligence Framework, structured around the adaptive cycle of Sense - Integrate - Analyze - Decide - Act - Learn, which shifts the focus of precision agriculture from technological deployment toward integrated and continuously improving decision intelligence. The framework emphasizes that technological value emerges when heterogeneous data are converted into accurate, timely, interpretable, and actionable recommendations that produce measurable agronomic outcomes. Methodologically, the integration of drone-based remote sensing, wireless sensor networks, multimodal data fusion, AI predictive modeling, field-level intervention, repeated outcome measurement, and human validation provides a comprehensive approach for evaluating the entire pathway from data acquisition to agricultural impact. This approach advances precision-agriculture research beyond isolated assessments of sensor performance or algorithmic accuracy by connecting technological performance directly with decision quality, field action, productivity, and resource efficiency.

The limitations of this study relate to the restricted number of agricultural settings, crop types, production cycles, and environmental conditions represented in the field implementation, which may limit the generalizability of the findings across heterogeneous farming systems. AI performance may also be influenced by data quality, sensor calibration, seasonal variability, model drift, connectivity limitations, and differences in local agronomic practices. Economic feasibility, long-term maintenance requirements, data governance, and the accessibility of advanced technologies for smallholder farmers require more extensive investigation before large-scale implementation can be recommended. Future research should conduct multi-season, multi-location, and cross-crop studies while incorporating longitudinal validation, cost-benefit analysis, explainable AI, uncertainty quantification, and comparative evaluation of alternative technological configurations. Greater attention should also be directed toward affordable and interoperable systems for smallholder agriculture, human–AI decision collaboration, and environmentally measurable outcomes. Such research can advance precision agriculture from fragmented digital monitoring toward an adaptive agricultural intelligence ecosystem capable of balancing productivity, economic viability, resource efficiency, and long-term environmental sustainability.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the author(s) used [NAME TOOL / SERVICE] in order to [REASON]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.

Author 2: Conceptualization; Data curation; In-vestigation.

Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

Apollon, W., Jean-Baptiste, Y., Maheshwari, S., Ghosh, S., Ghosh, S., Ariste, A., Joseph, R., Kamaraj, S.-K., & Bedair, H. (2026). Smart agriculture for greenhouse gas mitigation: Integrating digital tools, engineering metrics, and policy instruments—A review. *Next Research*, *7*, 101445. https://doi.org/10.1016/j.nexres.2026.101445

Bhardwaj, M., Kumar, P., & Singh, A. (2026). Bibliometric review of digital transformation in agriculture: Innovations, trends and sustainable futures. *Journal of Agribusiness in Developing and Emerging Economies*, *16*(4), 826–850. https://doi.org/10.1108/JADEE-02-2025-0083

Biswas, P., Kim, T. M., & Kim, W. S. (2026). Integration of digital twins and physical AI in cyber-physical systems. *Intelligent Systems with Applications*, *30*, 200649. https://doi.org/10.1016/j.iswa.2026.200649

Bitakou, E., Kotzabasaki, M., Psiroukis, V., Nychas, K., Demestichas, K., Bartzanas, T., Magazin, N., & Vujić, S. (2026). AI-driven approaches in precision agriculture for strawberry production: A systematic literature review. Smart Agricultural Technology, 14, 101944. https://doi.org/10.1016/j.atech.2026.101944

Boulealam, C., Filali, H., Mahraz, A. M., Tairi, H., & Riffi, J. (2026). Sugar beet detection using drone imagery. *Array*, *30*, 100952. https://doi.org/10.1016/j.array.2026.100952

Byrareddy, V. M., Baillie, J., & Scobie, M. (2026). A systematic review of digital twin technologies in broadacre agriculture: Challenges, opportunities, and sustainability. *Smart Agricultural Technology*, *14*, 102394. https://doi.org/10.1016/j.atech.2026.102394

Cheikhrouhou, S., Turki, M., & Dammak, B. (2026). X-FedAgriTwin: Privacy-preserving crop recommendation via Digital Twins and explainable federated learning. *Information and Software Technology*, *196*, 108173. https://doi.org/10.1016/j.infsof.2026.108173

El Hachimi, C., Belaqziz, S., Khabba, S., Karjoun, H., Kharrou, M. H., Hssaine, B. A., Er-Raki, S., Daccache, A., Chehbouni, A., & Weng, Q. (2025). Towards collective intelligence in agriculture: Deep reinforcement learning and digital twins for efficient management of collective irrigation water distribution systems. *Energy Nexus*, *20*, 100599. https://doi.org/10.1016/j.nexus.2025.100599

Elhoseny, M., Jahid, K., Latif, R., Saddik, A., & Atassi, R. (2026). Recent advances in IoT-driven crop monitoring and precision irrigation: Technologies, models, and future challenges. *Scientific African*, *31*, e03222. https://doi.org/10.1016/j.sciaf.2026.e03222

Eze, G., & Fiume, P. (2026). Chapter 2—Digital innovations in farming practices. In T. Ben Hassen & H. El Bilali (Eds.), *Digital Technologies for Sustainable Agriculture and Food Systems* (pp. 11–42). Academic Press. https://doi.org/10.1016/B978-0-443-33508-2.00005-0

Gueboudji, Z. (2026). Chapter 5—Nitrogen management using digital agriculture technology: A key for climate change mitigation. In T. A. Kurniawan & A. Anouzla (Eds.), *Point Source Nitrogen Pollution* (pp. 71–92). Elsevier. https://doi.org/10.1016/B978-0-443-27352-0.00007-0

Hashem, I. A., Zerdoumi, S., Jhanjhi, N., Siddiqa, A., & Foufou, S. (2026). Optimization and performance analysis of Drones and Unmanned Aerial Systems and Their Intelligence Applications. *International Journal of Cognitive Computing in Engineering*, *7*, 128–144. https://doi.org/10.1016/j.ijcce.2025.10.004

Khoshnodifar, Z., Ataei, P., & Karimi, H. (2025). Challenges of drone development in Iran's agricultural sector: The application of the TOWS analysis. *Cleaner Engineering and Technology*, *26*, 100950. https://doi.org/10.1016/j.clet.2025.100950

Kumar, R., Bagul, V. D., & Kumar, M. (2026). Chapter 3—AI in precision pest management and agricultural inputs. In N. A. Sagar, S. Agarwal, S. Sharma, V. Singh, & A. R. Jambrak (Eds.), *Artificial Intelligence Interventions in Agriculture, Food and Health Sectors* (pp. 65–90). Academic Press. https://doi.org/10.1016/B978-0-443-40501-3.00019-4

Kumar, S., Wani, A. W., Kaushik, R., Kaur, H., Djajadi, D., Khamidah, A., Saidah, Alasbali, N., Alreshidi, M. A., Alam, M. W., Yadav, K. K., & Wani, A. K. (2024). Navigating the landscape of precision horticulture: Sustainable agriculture in the digital Age. *Scientia Horticulturae*, *338*, 113688. https://doi.org/10.1016/j.scienta.2024.113688

Majdalawieh, M., Martins, C., Radi, M., Alaraj, M., & Khan, S. (2025). Precision agriculture in the age of AI: A systematic review of machine learning methods for crop disease detection. *Smart Agricultural Technology*, *12*, 101491. https://doi.org/10.1016/j.atech.2025.101491

Mamabolo, E., Mashala, M. J., Mugari, E., Mogale, T. E., Mathebula, N., Mabitsela, K., & Ayisi, K. K. (2025). Application of precision agriculture technologies for crop protection and soil health. *Smart Agricultural Technology*, *12*, 101270. https://doi.org/10.1016/j.atech.2025.101270

Manimozhian, A., & Chandel, A. K. (2026). Thermal infrared technologies for precision agriculture: A ROSES-guided systematic evidence synthesis on platforms, calibration, and digital analytics. *Agricultural Environment and Sustainability*, *1*(2), 100014. https://doi.org/10.1016/j.ages.2026.100014

Mehrotra, S., Mishra, S., Srivastava, V., Yadav, D., & Singh, V. (2026). Digital dimension of plant science research: A bird's eye view of AI integration. *Plant Science*, *371*, 113297. https://doi.org/10.1016/j.plantsci.2026.113297

Morchid, A., Kabbaj, M. N., & Benbrahim, M. (2026). Precision irrigation based on IoT and energy management: Driving future sustainable water management in farming. *Renewable and Sustainable Energy Reviews*, *240*, 117179. https://doi.org/10.1016/j.rser.2026.117179

Morgan, H., Elgendy, A., Tran, B., Ismail, T., Moursy, M. M., Shehadeh, Y. Kh., ElGharib, A., Al-Dughairi, A. A., Mubarak, A. E., Harhash, K. A., & El-Askary, H. (2026). AI-driven multispectral drone monitoring for afforestation in arid environments. *Results in Engineering*, *30*, 110792. https://doi.org/10.1016/j.rineng.2026.110792

Moussaid, A., Mousannif, H., Gamoussi, Y., & Briak, H. (2026). Advanced artificial intelligence and remote sensing for earth observation–based tree crop monitoring: A global review with african perspectives. *Neurocomputing*, *700*, 134165. https://doi.org/10.1016/j.neucom.2026.134165

Nath, M. K., Mookkandi, K., Balakrishnan, K., Mishra, M., Kavitha, M., & Mathumathi, M. (2026). Bottleneck of AI driven techniques for identifying indian agricultural diseases: A systematic review and future directives. *Results in Engineering*, *31*, 111212. https://doi.org/10.1016/j.rineng.2026.111212

Rahimzad, M., Homayouni, S., & McNairn, H. (2026). Active and incremental learning with RAUNet for advancing soil cover monitoring from mobile digital imaging through deep learning. *Computers and Electronics in Agriculture*, *253*, 112161. https://doi.org/10.1016/j.compag.2026.112161

Rai, N., (Dana) Choi, D., Boyd, N. S., & Schumann, A. W. (2026). Advancing site-specific disease and pest management in precision agriculture: From reasoning-driven foundation models to adaptive, feedback-based learning. *Computers and Electronics in Agriculture*, *250*, 111859. https://doi.org/10.1016/j.compag.2026.111859

Rayamajhi, A., Jahanifar, H., & Mahmud, M. S. (2024). Measuring ornamental tree canopy attributes for precision spraying using drone technology and self-supervised segmentation. *Computers and Electronics in Agriculture*, *225*, 109359. https://doi.org/10.1016/j.compag.2024.109359

Rehman, M. U., Eesaar, H., Abbas, Z., Seneviratne, L., Hussain, I., & Chong, K. T. (2024). Advanced drone-based weed detection using feature-enriched deep learning approach. *Knowledge-Based Systems*, *305*, 112655. https://doi.org/10.1016/j.knosys.2024.112655

Storm, H., Seidel, S. J., Klingbeil, L., Ewert, F., Vereecken, H., Amelung, W., Behnke, S., Bennewitz, M., Börner, J., Döring, T., Gall, J., Mahlein, A.-K., McCool, C., Rascher, U., Wrobel, S., Schnepf, A., Stachniss, C., & Kuhlmann, H. (2024). Research priorities to leverage smart digital technologies for sustainable crop production. *European Journal of Agronomy*, *156*, 127178. https://doi.org/10.1016/j.eja.2024.127178

Subeesh, A., & Chauhan, N. (2026). Agricultural digital twin for smart farming: A review. *Green Technologies and Sustainability*, *4*(2), 100299. https://doi.org/10.1016/j.grets.2025.100299

Talaeizadeh, A., Sharifi, I., Alasty, A., & Ghatrehsamani, S. (2025). Agricultural spraying drones: A comprehensive review. *Smart Agricultural Technology*, *12*, 101519. https://doi.org/10.1016/j.atech.2025.101519

Vahidi, M., Shafian, S., & Frame, W. H. (2025). Multi-Modal sensing for soil moisture mapping: Integrating drone-based ground penetrating radar and RGB-thermal imaging with deep learning. *Computers and Electronics in Agriculture*, *236*, 110423. https://doi.org/10.1016/j.compag.2025.110423

Volpato, L., Wright, E. M., & Gomez, F. E. (2024). Drone-Based Digital Phenotyping to Evaluating Relative Maturity, Stand Count, and Plant Height in Dry Beans (Phaseolus vulgaris L.). *Plant Phenomics*, *6*, 0278. https://doi.org/10.34133/plantphenomics.0278

Xia, X., Sachar, J., Alibhai, K., Labelle, J., Demin, D., Sulle, E., & Kim, W. S. (2025). Accessible drone image processing for sustainable resource management of 3D tree-like crops using unsupervised algorithms. *Information Processing in Agriculture*. https://doi.org/10.1016/j.inpa.2025.11.009

Xu, C., Zhao, L., Wen, H., Zhang, Y., Wang, L., & Zhang, L. (2026). Intelligent management of crop diseases and pests in multiscale and multimodal complex scenarios: Technologies, applications, and prospects. *Computers and Electronics in Agriculture*, *244*, 111443. https://doi.org/10.1016/j.compag.2026.111443

Yan, Y., Song, F., & Sun, J. (2025). The application of UAV technology in maize crop protection strategies: A review. *Computers and Electronics in Agriculture*, *237*, 110679. https://doi.org/10.1016/j.compag.2025.110679

Yang, Z., & Tang, T. (2026). Closing the loop: AI-driven integration of multi-omics and phenomics for systematic resilient crop engineering. *Biotechnology Advances*, *90*, 108908. https://doi.org/10.1016/j.biotechadv.2026.108908