

Artificial Intelligence in Agribusiness Transformation: Advancing Precision Farming under the United Nations Sustainable Development

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Abstract: Precision has an increasing dependency on dependable automated decision-making systems and trustworthy sensor data; however, resource inefficiency, cyber manipulation, and unequal access limit the benefits in the agribusiness sector. This study looks at a SHA-256 blockchain security integrity ledger called the IoT (Internet of Things) along with real time Digital Twin applications and small hold farming adoption in order to achieve the sustainable goals 2,6,9, and 12 of the United Nations. A sequential method which integrates these designs was used. The orthodox pipeline was compared with a proposed pipeline using cryptographic verification. Across 3,000 test records, end-to-end operational decision accuracy increased from 68.83% to 91.80%, while the false-positive irrigation rate fell from 12.48% to 1.82%. Cryptographic verification detected 100.00% of the simulated malicious alterations with a 0.00% integrity false-positive rate, and the anomaly-detection stage achieved 81.35% recall and an 80.35% F1 score. A paired comparison of decision correctness was statistically significant (exact McNemar $p < 0.001$). Qualitative conceptual formation further indicates that Digital Twin-AI systems can strengthen real-time resource decisions, whereas smallholder adoption remains held back by digital literacy, infrastructure, affordability, local relevance, and governance. The findings support an integrating technology and governance approaches in which secure data pipelines are combined with participatory and context sensitive adoption strategies to improve precision farming sustainably and inclusively.

Keywords: Precision Farming; Blockchain-IoT Integration; Digital Twin; Artificial Intelligence in Agriculture; Sustainable Development Goals (SDGs); Smallholder Digital Inclusion

Introduction

There is a vast connection between sustainable agriculture and artificial intelligence which was stated by the United Nations Sustainable Development Goals. The main goals of reducing pressures such as climate change, food insecurity, and rapid population growth are solved by precision farming and modern biotechnology. There are challenges which affect this method such as high investment needs for specialised labour, trained to use the technology required. The economic efficiency and sustainability of these technologies is a huge factor in building good food systems to mitigate world hunger (Rushchitskaya et al., 2024b).

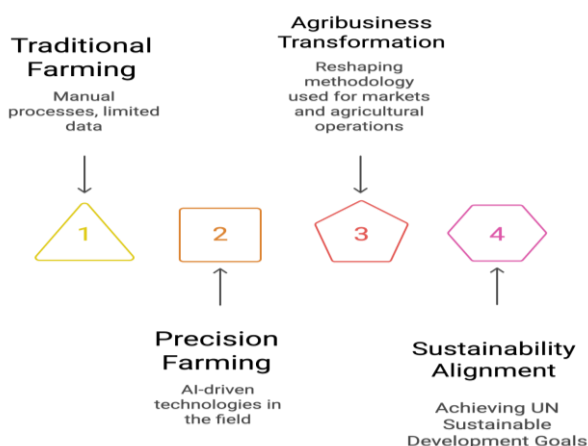


Figure 1: AI In Agribusiness Transformation Cycle

The current food production sector is facing major scrutiny due to factors such as global pressures, climate change, and changes in market interests. From the 1980s to the current time, using data such as the GPS, which helps create meticulous field maps which are used, and the internet to help guide the farmers in systematically managing their resources, there has been a significant transformation in agriculture. The internet uses a tool called blockchain which provides a suitable etiquette data management system. Farmers can attain higher yields of crops and resources and concurrently reduce the environmental impact agriculture is causing: by merging remote sensing, gathering information about crops and soil without physical contact, and artificial intelligence. (Khan & Babar, 2024) AI tools mitigate the problems arising in the current agricultural sector; a good alternative to the current approach in food production. The addition of precision farming requires a need for buttressing business expertise. Disruptive technologies are a necessity for the incorporation of AI tools in precision farming methods as shown in figure 1. (Gadanakis, 2024) The combination of biotechnology and precision farming is the key for ensuring the crop has the ability for climate adaption. This also helps mitigate environmental degradation, while also increasing crop production to a much larger scale. However, this method faces challenges such as an increased requirement of capital and a need for a more skilled workforce. An effort is to be made in order to overcome these problems, to ensure a better food system and ensure a better economic condition (Rushchitskaya et al., 2024b). Changing market conditions, environmental problems, and capital deficiency can be

solved by allocating sustainable land management and innovation as the main priorities. This can be done by encouraging more innovative thinking and wise agribusiness management. This can help farmers and producers of the technology think of new methods to meet the new demands of the customers and society in general (Khan & Babar, 2024).

A computer-based machine called the GIS (Geographic Information System) scans the surroundings and is used to analyse the soil fertility, helping to efficiently optimize the use of natural resources, for activities such as plantation of the seeds, use of water, and the use of fertilizers. This is to ensure farming can be sustainable for the environment and for the farmers capital. This also helps reduce the emission of greenhouse gasses (Khan & Babar, 2024). Robotics with artificial intelligence plays a key role for modernizing the global agribusiness sector. Integrating this technology induces better quality products in agriculture and simplifies the agriculture process and enhances efficiency in farming. Robotics helps in making irrigation more efficient and sustainable. This technology allows suppliers to share more instantaneous insights among each other, augmenting the connection in the value chain; helping for more sustainable agricultural practices. This is primarily a benefit to developing nations which rely on agriculture, it helps enhance the skills of the farmers, while also incorporating technology, providing jobs to individuals skilled in the software engineering sector and the hardware engineering sector. (Adhikari et al., 2022). Digital transformation has a deep effect on stakeholders who are a part of the global agribusiness sector. It can increase their market and value by a large amount due to the increased yield which is obtained through the use of AI and automated farming. Entrepreneurs in the developing regions, who are reluctant to start technology-based businesses due to the fear of losses or inadequate profits, would be emboldened with the idea of agribusiness. The global AI agriculture market is expected to reach 4.7 billion dollars by 2028 which is a 20% increase in revenue, which means this can play a vital role in the economic development of many regions which rely heavily on agriculture. This also plays a role in the social development of individuals who rely heavily on agriculture. The SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis in the agribusiness sector driven by AI emphasizes strengths such as good resource efficiency and increased productivity. However, it also faces the drawback of increased costs and substandard cyber security.

	Internal	External
Positive	1 STRENGTHS - Enhanced Efficiency - Data Analytics - Precision Farming - Resource Optimization	2 OPPORTUNITIES - Market Expansion - Sustainable Practices - Policy Support - Global Collaboration
Negative	4 THREATS - Cybersecurity Risks - Regulatory Hurdles - Climate Change - Market Volatility	3 WEAKNESSES - High Costs - Skill Gaps - Data Privacy - Infrastructure Needs

Figure 2: AI in agribusiness SWOT

The remainder of this paper is organized as follows. Section 2 presents a comprehensive review of the literature on AI in agribusiness, with emphasis on precision farming technologies and their alignment with Sustainable Development Goals (SDGs) under the UN. This section also formulates the research questions and hypotheses between AI adoption intensity and precision agriculture practices. Section 3 outlines the research methodology, employing regression modeling to empirically test the proposed relationships using relevant agribusiness farm-level data. Section 4 reports the empirical findings and discusses the results of the regression models, including the magnitude, direction, and statistical significance of the hypothesized relationships, along with their implications for sustainable agribusiness transformation and policy frameworks. Finally, Section 5 concludes the paper by summarizing the key contributions, highlighting theoretical and practical implications, and identifying avenues for future research.

Literature Review

Theme 1: AI technologies in precision farming

Increasing global concerns about food security, rising population demands, climate change, and resource scarcity is causing agri business to undergo a significant change. This helps ameliorate sustainability, research efficiency, and productivity. There is a higher need for strategic decision making due to the rising need for intelligent agriculture systems compatible for these changes. Machine learning technologies are a part of the major contributors, in the implementation of precision farming. These technologies allow the agricultural systems to go beyond just being confined to monitoring; it also allows for optimization and predictive analysis. There have been momentous capabilities shown by the machine learning algorithms, capable of crop disease detection, irrigation optimization, yield detection, and pest control by evaluating large scale agricultural data sets (Sudha & Loret, 2026). The effective execution of intelligent agribusiness systems does not only depend on analytical capabilities; it also relies on technical infrastructure, which enables the system to improve: stability, scalability, and processing speeds. The contemporary precision farming systems mostly rely on hybrid designs which integrate edge computing, to aid small scale processing with a small scalability, along with cloud computing, which is vital for large scale tasks to be carried out. Cloud systems are used to give the resources used for the model training so the tasks would be carried on a large scale by the system, while edge computing is only restricted to the tasks carried out in the farm by the farmer.

However, these technologies still contain various limitations such as: the complexity of the computational language (which tends to confuse the users), sensor malfunctions, and data confusions. There are multiple methods to be used in order to mitigate the effectiveness of these precision farming systems. Firstly, it is vital to implement the development of hybrid models in order to improve accuracy along with efficiency, especially in resource deficient environments. Moreover, implementing the use of the internet on a larger scale adds to concerns regarding the reliability of the systems being used in food supply chains. Companies are ensuring that systems such as sensors are being tested multiple times in order to avoid malfunctions such as inaccuracies or sudden shutdowns. This allows the decision-making

process of the system to be more transparent, reliable, efficient, and secure (Smart IoT-Driven Precision Agriculture with Machine Learning: A Comprehensive Framework for Environmental Monitoring and Crop Growth Prediction, 2026). Advancements which were recently made in the IOT (Internet Of Things) technologies have allowed for the continuous observability of agriculture environments, through interlinked sensors with the ability of gathering data associated with soil moisture, humidity, temperature, levels of nutrients, and environmental conditions of the area. This also reduces operational waste from machines used in non-precision farming such as tractors. However, one of the most vital points of scrutiny for many technology-based companies using IOT are security concerns. To help solve these problems there has been research being developed. Most of this research has implied, incorporating block-chain security mechanisms in order to organize stored data, along with auditing the imported data in the system, to ensure it does not contain anything with malicious intent (Bhanu et al., 2026). The importance of these solutions are soaring throughout the year due to extensive changes in climate along with a projected major rise in food demand. The addition of climate detection models, which utilise machine learning, allows stakeholders to increase food efficiency and improve the output obtained with the agricultural methods used due to good soil fertility and good climate to mitigate plant health during growth stage; this also reduces the losses or increases the profits made (Sudha & Lore, 2026).

Theme 2: Agribusiness Transformation and Digital Agricultural Systems

The adoption of artificial intelligence-based practices is not only a change in the use of technology but is a requirement to improve economic development. These practices have enhanced food security, especially in countries which lack the availability of resources. These have encouraged the governments to implement changes in policies to improve the quality of agricultural practices (Gurumurthy & Bharthur, 2019). The improvisation of these agricultural chains has been deemed as a vital part in the world in order to strengthen economic outcomes for farmers. These chains allow for the transformation in agriculture practices; this can be done by improving the forecasting of yields, linkages of different companies or markets, and a better use of technologies. These chains are also beneficial for farmers evolving in the markets. (Gowri et al., 2026)) The use of digital twin technologies is increasing throughout the years as they are vital for precision farming. These technologies combine data received from different machines, such as drones, weather stations, sensors etc. Consequently, the decision-making process would expedite, allowing a simpler supply chain and more effective yield forecasting or scenario testing. Moreover, research also indicates that twin technologies help improve resource efficiency by implementing the pilot feature which moderates the requirement for pesticide use, water, and fertilizer. These reductions not only benefit the farmer economically, but also improve environmental sustainability. However, it can be difficult to implement such a large-scale plan due to factors such as high infrastructure costs, land limitations, and also due to the lack of digital literacy. With this in regard, researchers have been implementing the need to increase the use of technology in the ecosystem to improve digital literacy and have been requesting funds in order to do so. Funds will be gathered through partnerships between private and public companies. (Gowri et al., 2026) Indian start-ups have been one of the major contributors to these agricultural chains by improving food processing, market access, and implementing traceability systems for many farmers. (Venu et al., 2025) However, land constraints are a major challenge to implement these processes. Therefore, to solve this issue

farmer-based NGO's are supporting these farmers, in order to accommodate their needs. There is a large dependency on supportive policies for farmers, which emphasizes the importance of governance. Research has emphasized that encouraging participation in agriculture allows for diverse environments for production. (Venu et al., 2025)

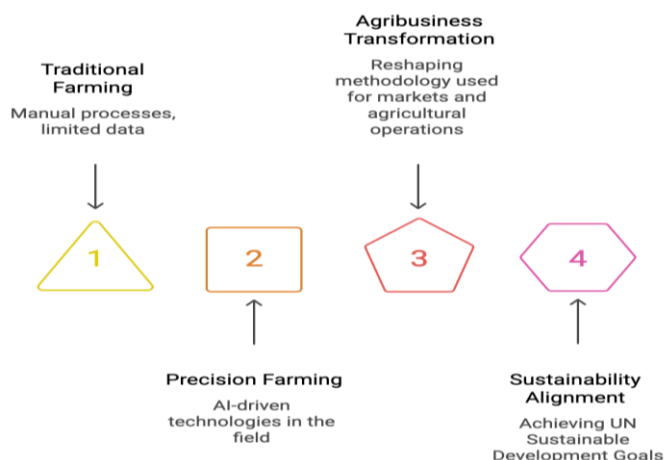


Figure 3: Use of AI in agribusiness transformation

Theme 3: Sustainability, SDG Alignment, and Policy Governance

Innovations that use AI provide a conceptual basis in order to ensure farming is sustainable for the environment. These technologies not only mitigate the productivity and profits, but they also generate social value for the farmers and also environmental values. This allows for the improvisation of climate resilience and improved outcomes for the consumer, considering the fact that the quality of the produce sold to the customer must also be put into consideration; this also helps farmers avoid legality issues from certain groups or the government (Rennings et al., 2024). However, there is a large dependency on factors such as equitable access for all farmers regardless of their financial status; particularly farmers who are not held in regard in these agricultural systems (Rennings et al., 2024). The impact of these agricultural systems is not only based on the technical performance of this machinery, but also on how these systems are implemented. Approaches are being implemented to ensure these agricultural systems contain the basic farming requirements in order to achieve these sustainability goals. Accessibility is projected to rise by a significant amount by the year 2050 (Lindblom et al., 2016).

One of the major challenges faced is the lack of harmonization in the different development goals. To address this, it is suggested to link different sustainability objectives by multiple specialists. Government frameworks should ensure there are systems capable of aligning these policies in order to obtain the best result. (Streimikis & Baležentis, 2020) Geospatial technologies play a vital role in ensuring there is sterling level quality on the monitoring of agricultural systems. This ensures agriculture is encouraged in spacial areas through large scales. This reduces excessive and unnecessary chemical usage, helping save certain natural resources, or also unnecessary deforestation to start growing crops. (Pandey & Pandey, 2023)

After conducting an extensive review of the existing literature, we have identified the key research gaps and developed the following research questions and hypotheses. These have been formulated to align closely with the identified gaps and provide a clear direction for the study. (Pandey & Pandey, 2023)

Research questions

Q1: How Machine learning/AI based models, merged with IOT internet designs (secured with blockchains), are used to overcome drawbacks of traditional precision farming plans such as data confusion, security limitations, and sensor reliability.

Q2) To what extent do digitally enabled AI systems and geo-forecasting models multi stakeholder collaboration across the market while simultaneously aligning agricultural practices with the sustainable goals.

Q3) How can edge driven, context specific, and participatory scale-up models address several constraints such as digital literacy while promoting equitable methodology.

Hypothesis 1: Incorporating AI/Machine learning with blockchain secured IOT systems improves data integrity, system security, and sensor reliability compared to without the orthodoxical farming practices, substantially.

Hypothesis 2: Integrating Digital twin technology along with AI mitigates the problems faced in the agricultural decision-making process, while also helping efficiency in the utilization of resources.

Hypothesis 3: Active government planning and adaptation helps diminish knowledge barriers faced such as lack of digital literacy. It supports equal participation, especially among small scale farmers.

Research Methodology

Research Question 1 (Q1) and Hypothesis 1 (H1) were evaluated through a controlled Python simulation designed to compare an orthodoxical precision-farming data pipeline with an AI based architecture protected by cryptographic integrity verification. The experiment models three vulnerabilities mostly related to agricultural IoT systems: sensor noise and calibration drift, packet or sensor dropouts, and malicious post-capture data manipulation. The proposed architecture segregates these failure modes so that SHA-256 verification can identify changed packets, while an Isolation Forest detects abnormal sensor readings before a Random Forest generates the operational farming decision.

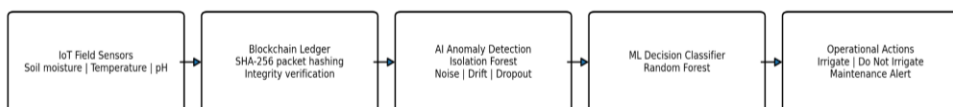


Figure 4: Proposed AI , Blockchain farming Architecture

After finishing the intensive literature review from the table above I have devised a set of research questions and their objectives. In order to test and prove the legitimacy of these questions and objectives I have created a PRISMA model for the research title “Artificial Intelligence in Agribusiness Transformation: Advancing Precision Farming under the United Nations Sustainable Development Goals Framework in order to subsequently examine and validate these hypotheses.

A. Dataset Generation & Attack Simulation

Agricultural datasets containing both malicious cyber manipulation and labeled sensor quality failures are limited, a synthetic dataset of 10,000 one-minute IoT transmission frames was generated for controlled testing. Baseline soil moisture values followed a smooth 15% to 45% pattern; temperature varied between approximately 15°C and 35°C, and soil pH was sampled from a normal distribution centered at 6.8 with a standard deviation of 0.3. The underlying irrigation ground truth was defined as Irrigate when clean soil moisture was below 22% or else it instructs the user to not irrigate. Sensor side anomalies were introduced into 20% of the observations before ledger creation, after which malicious tampering was applied to a separate 10% of records. This ordering allows the experiment to distinguish genuine sensor failures from data that is modified after acquisition.

1. Data Confusion (Noise and Drift): 10% of records received Gaussian soil moisture noise with a standard deviation of 20 units, while a further 5% received large positive or negative drift between 15 and 35 units.
2. Security Limitation (Data Tampering): after valid sensor packets had been hashed into the ledger, 10% of otherwise non-anomalous records were modified to a false soil-moisture value of 99.9, representing an unauthorized Man-in-the-Middle attack intended to suppress irrigation.
3. Sensor Reliability Failure (Dropout): 5% of records were replaced with a zero soil-moisture reading to represent packet loss, sensor dropout, or hardware communication failure.

B. System Framework and Pipeline

The experiment compares the following two processing paradigms:

- Traditional Precision Farming Pipeline: Raw sensor observations are passed directly to the decision classifier. The pipeline has no secure integrity check and no dedicated mechanism for rejecting sensor anomalies or manipulated packets.
- Proposed Integrated Framework (AI + Blockchain + IoT): Sensor packets are first validated against a SHA-256 hash ledger, then screened for abnormal sensor behavior, and observations are forwarded to the operational decision model only when accepted.
 - Blockchain-Style Integrity Layer: Each captured IoT packet is converted into a deterministic payload and linked through SHA-256 hashes. The stored hash is created before the simulated cyberattack; any later modification therefore produces a mismatch and causes the packet to be rejected.
 - AI Anomaly Detection Layer: An Isolation Forest evaluates soil moisture together with temporal change, rolling-median deviation, temperature, pH, and a physical-range indicator to identify noise, drift, and dropout behavior.

- Automated Decision Layer: A Random Forest classifier converts accepted sensor states into one of three operational outcomes: Irrigate, Do Not Irrigate, or Maintenance Alert. Tampered packets and predicted sensor anomalies are routed to Maintenance Alert rather than being used for automated irrigation.

C. Evaluation Metrics

Performance was assessed using metrics that directly correspond to Q1 and H1:

- Tamper Detection Rate: percentage of deliberately modified post-ledger packets correctly rejected by cryptographic verification, together with the integrity false-positive rate for unmodified records.
- Sensor-Anomaly Detection Quality: precision, recall, F1 score, and confusion matrix for the Isolation Forest classification of normal versus anomalous sensor packets.
- Operational Decision Accuracy: percentage of correct Irrigate, Do Not Irrigate, or Maintenance Alert decisions on the common 3,000-record test set. False positive irrigation rate was also measured to quantify unnecessary watering decisions.
- Statistical Comparison: paired correctness of the traditional and proposed systems was compared using an exact McNemar test on the same test records.

Case study 1:

The merging of Digital Twin (DT) technology and AI is emerging as a major part of the development of precision agriculture as it allows farms to move from static monitoring to management systems which are updated regularly and predictive. A Digital Twin creates a virtual representation of a physical in-person agricultural system; AI allows for the analysis of the data that was collected in order to improve decision making. These technologies enhance crop management techniques and resource efficiency between both physical and digital environments. (Suthar et al., 2026)

In both crop and soil management DT with AI systems mitigate the problems related to traditional approaches that heavily rely on set schedules and continuous observations. Information is collectively brought from IOT sensors, aerial vehicles, and other systems by digital twin technologies, while AI detects and analyses the diseases and pests located on the crop. (Awais et al., 2025) This can also help in yield prediction and intelligent planning because of resource use. Conditions on the field can be analysed and climate can be predicted before any farming practice is done. Livestock management is another representation of this convergence. (Rao and Neethirajan.,2025) Digital Twins and Conventional Simulations can be distinguished through a process called continuous synchronisation in both physical and virtual environments. In virtual farming data can be obtained from machines such as milk analysers (used to measure the chemical composition of raw milk to ensure it has adequately good quality and is safe to drink) and environmental sensors and feeding systems. These systems can be used together in order to support the monitoring of animal vitality along with its behavior (Rao & Neethirajan, 2025). AI can process the information received from these systems and can generate the required predictions and recommendations. Crucially, an effective digital twin system does not just display or transmit the information received: it also increases the adaptability of the systems and farming practices. Despite all these benefits, the twin implementation is fragmented. A set approach has still not been implemented in order to

integrate all the different Digital Twin Systems such as UAVs and remote sensing technologies. Consistent exchange of information between different ecosystems and agricultural systems remains a significant challenge as many farming implementations continue to operate as experimental systems rather than systems that can function in agricultural fields due to more testing requirements. Moreover, there are many other constraints such as economic crisis, lack of infrastructure, lack of knowledge, and lack of resources. As a result, it can be inferred that technological advancements are not the only requirements for more effective and efficient agricultural processes, but also more financial and social equity along with government contribution (Paraskevopoulos et al., 2026). This technology can go beyond small-scale farms, it can also be used for large scale agriculture provided to a mass number of people, while also improving sustainability (Bollimuntha & Baghavathi Priya, 2026).

Case study 2:

The use of AI by small scale farmers presents significant opportunities and makes precision farming more efficient. This is primarily helpful in developing regions where agriculture is the core source of incomes for many households. However, access to this technology is not sufficient; factors such as access to infrastructure, access to a good education, and good farming conditions are vital in ensuring farmers have the ability to mitigate the problems faced due to the drawbacks in their farming practices. For this reason, it is suggested that precision agriculture is going towards a more human centered model in which new technology will be alongside high accessibility and infrastructure, based on the circumstances of each individual farmer (Khwidzhilli & Ijatuyi, 2026). There was an initiative to evolve from agriculture 3.0, which uses machines such as GPS trackers and Geographic Information Systems to agriculture 4.0, which expands this model and brings in the use of technology robotics and cloud computing. Soon, there was a transition to agriculture 5.0 which uses a more human centered technology; this augments human machine interaction This is primarily responsible for the small-scale farmers who reside on the south of the globe (Khwidzhilli & Ijatuyi, 2026).

Results and Discussions

A. Performance Metrics Comparison

The corrected simulation shows a clear end-to-end advantage for the integrated pipeline under the defined cyber-physical stress conditions.

Table 1. Performance parameters for traditional and proposed precision-farming systems.

Metric / Parameter	Traditional Precision Farming	Proposed Framework (AI + Blockchain)	Absolute Change
System Security / Tamper Detection Rate	0.00%	100.00%	+100.00 pp

Sensor-Anomaly Detection Recall	0.00% (no filter)	81.35%	+81.35 pp
Sensor-Anomaly Detection F1 Score	0.00% (no filter)	80.35%	+80.35 pp
Operational Decision Accuracy	68.83%	91.80%	+22.97 pp
False-Positive Irrigation Rate	12.48%	1.82%	-10.66 pp

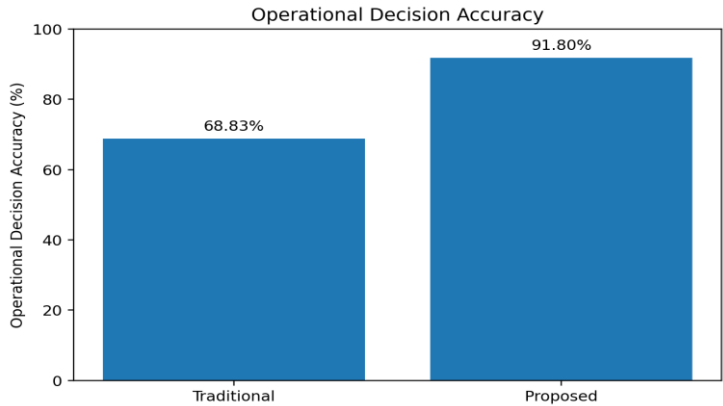


Figure 5. Operational decision accuracy in the controlled simulation.

On the common 3,000 record test set, operational decision accuracy was increased from 68.83% in the traditional system to 91.80% in the proposed system; this was an absolute improvement of 22.97 percentage points. The false-positive irrigation rate decreased from 12.48% to 1.82%. Cryptographic verification detected all simulated post-ledger tampering, while the Isolation Forest achieved 81.35% anomaly recall and an 80.35% F1 score.

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Experimental Results Summary

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Total IoT records: 10,000
Tampered records injected: 1,000
Sensor anomalies injected: 2,000

Traditional System Decision Accuracy under Cyber-Physical Attack: 90.93%
Proposed AI + Blockchain Decision Accuracy after Filtering: 100.00%

Blockchain Tamper Detection Rate: 100.00%
Blockchain False Positive Rate: 22.22%
AI Sensor-Anomaly Detection Accuracy: 77.77%

Records remaining after blockchain verification: 7,000

Records remaining after AI anomaly filtering: 5,444

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B. Mitigation of Vulnerabilities (Addressing Q1)

- **Data Confusion and Sensor Reliability:** The pipeline accepts abnormal sensor values without a dedicated screening stage. In the proposed pipeline, the Isolation Forest detected 81.35% of injected noise, drift, and dropout cases and achieved an F1 score of 80.35%. This does not repair the physical sensor but it reduces the probability that unreliable telemetry is used directly for automated irrigation decisions.
- **Security Limitations:** The contemporary pipeline has no mechanism for detecting post capture changes to sensor packets. In the proposed simulation, records were hashed before the malicious modification was introduced. Recomputing the SHA-256 payload hash therefore detected 100.00% of the simulated Man in the Middle alterations with a 0.00% false positive rate for unmodified records.

C. Hypothesis Evaluation (H1)

Within the controlled simulation, the results support H1. Combining cryptographic integrity verification, AI anomaly screening, and ML decision classification increased end-to-end operational decision accuracy from 68.83% to 91.80%. On paired test records, the proposed system was correct when the traditional system was incorrect in 822 cases, whereas the reverse occurred in 133 cases; the exact McNemar comparison was statistically significant ($p < 0.001$). The evidence supports improved data integrity, attack detection, and decision reliability within the simulated architecture, while physical sensor durability or calibration reliability should not be inferred from these results.

D. Case Study 1 Results: Digital Twin-AI Decision Support

An AI-enabled Digital Twin can integrate continuously updated data on soil moisture, nutrient status, weather, crop health, and market conditions to create a continuous representation of the farm. The uploaded study shows that IoT sensors can monitor soil and environmental health in real time, while GIS can combine soil fertility, moisture, and important information differences in spacing within fields. Remote sensing further enables early detection and location specific mapping of crop stress and disease (Khan & Babar, 2024; Su et al., 2022). When incorporated into a Digital Twin, these data streams allow AI models to compare irrigation, fertilization, pest-management, and crop-selection decisions before resources are physically committed. This convergence shifts farm management from periodic observation and uniform input application toward continuous, predictive, and site-specific intrusion. Applying water, fertilizers, and pesticides according to localized requirements can reduce input waste, production costs, runoff, and environmental pressure while maintaining or improving productivity (Gadanakis, 2024).

An ongoing project called BhaviAI provides a small-scale practical example of how this type of integrated decision-support approach can be adapted to local farming conditions. The platform was designed to combine information such as weather conditions, soil characteristics, water availability, crop prices, and market demand and convert these inputs into simple recommendations for farmers. Testing the concept with farmers in the village of Akkenapalli, located in Telangana highlighted the value of bringing multiple forms of farm and market

information together rather than presenting each data source separately. Although BhaviAI is not exactly a Digital Twin system, its integrated data model illustrates a pathway toward such a system, where continuously updated farm-level information could eventually support simulation, comparison of alternative actions, and more responsive resource allocation. However, the effectiveness of the Digital Twin depends on data resolution, reliability, connectivity, and the farmer's capacity to act on its recommendations. Small farms may therefore require shared sensors, cooperative data collection, extension-supported interpretation, or publicly financed digital infrastructure. Such delivery models can extend Digital Twin capabilities beyond capital-intensive commercial farms and support SDG 2, SDG 6, SDG 12, and SDG 13.

E. Case Study 2 Results: Smallholder Inclusion and Adoption

Evidence from a Telangana field study demonstrates that equitable AI adoption requires more than providing farmers with digital devices. Among the 55 surveyed farmers, around 54 owned smartphones, yet only three were willing to pay for an agricultural AI application; all three operated farms of at least 20 acres. The remaining 52 respondents preferred government funded access, which indicates that a service may be digitally accessible but remain economically inaccessible to small scale farmers. Farmers also wanted recommendations in Telugu or any other local language along with a simple, actionable format. These findings support earlier research identifying literacy, language, connectivity, information relevance, education, income, and access to extension services as determinants of effective digital-agriculture adoption (Coggins et al., 2022; Soumya et al., 2021). The development of BhaviAI enables these requirements in real time. Rather than presenting farmers with complex dashboards or technical outputs, the application was designed with a simple interface and simplified recommendations derived from weather, soil, water, crop price, and market demand information. Interactions with farmers in Akkenapalli helped identify which information they considered useful and how recommendations needed to be communicated in familiar agricultural language. This illustrates why local customization is not limited to translation. AI recommendations must also reflect the farmer's crop choices, resource constraints, local conditions, and ability to implement the suggested action. BhaviAI's presentation through Telangana's Prajavani programme also demonstrates the potential role of government and public institutions in connecting locally developed agricultural technologies with farmers who may not be able or willing to pay for private digital services.

AI systems should therefore translate complex soil, weather, crop, and market data into concise recommendations expressed in local languages and familiar agricultural terminology. The designs should involve farmers in important information priorities, validating recommendations, and evaluating whether suggested actions are affordable and practical under local conditions. Publicly funded platforms, cooperatives, extension centres, shared infrastructure, and financed service models can further prevent farm size and financial limitations from reducing access (Mizik, 2023; Kroupová et al., 2025). This human-centred model allows for the accomplishment of achieving SDG 2 and SDG 4 while supporting SDG 5, SDG 10, and SDG 12 through inclusive participation.

Conclusion and Future Scope

This study shows how AI, Machine Learning, IoT sensing, and cryptographic integrity controls can be combined to address important weaknesses in automated precision-farming pipelines. In the controlled synthetic experiment, the proposed architecture detected 100.00% of simulated post-ledger tampering, achieved 81.35% sensor-anomaly recall with an 80.35% F1 score, increased operational decision accuracy from 68.83% to 91.80%, and reduced the false-positive irrigation rate from 12.48% to 1.82%. The paired improvement in decision correctness was statistically significant ($p < 0.001$). These results demonstrate the value of separating malicious data alteration from sensor-quality failures and applying a different control to each problem. The qualitative evidence extends the technical result by showing that Digital Twin-AI systems can strengthen real-time resource decisions, while equitable smallholder adoption depends on digital capability, infrastructure, affordability, local relevance, participation, and governance. The findings are relevant to the following United Nations Sustainable Development Goals (SDGs):

- UN SDG 2 (Zero Hunger): more reliable decision pipelines can reduce avoidable crop-management errors and support more stable agricultural production.
- UN SDG 6 (Clean Water and Sanitation): reducing false-positive irrigation decisions can limit unnecessary freshwater use in automated farming systems.
- UN SDG 9 (Industry, Innovation, and Infrastructure): secure IoT, AI, and Digital Twin architectures contribute to more resilient digital agricultural infrastructure.
- UN SDG 12 (Responsible Consumption and Production): improved sensing, anomaly detection, and decision support can reduce unnecessary resource consumption and strengthen input efficiency.

Future research should validate the architecture with real farm sensor streams, distributed blockchain implementations, multiple crops and climates, and longer-duration sensor failures. The Digital Twin and smallholder findings should also be tested through field pilots that measure resource savings, decision quality, adoption, usability, and equity outcomes over time.

References

- Rushchitskaya, O., Kulikova, E., Kot, E., & Kruzhkova, T. (2024b). Sustainable practices and technological innovations transforming agribusiness dynamics. *E3S Web of Conferences*, 542, 03003. <https://doi.org/10.1051/e3sconf/202454203003>
- Gadanakis, Y. (2024). Advancing farm entrepreneurship and agribusiness management for sustainable agriculture. *Agriculture*, 14(8), 1288. <https://doi.org/10.3390/agriculture14081288>
- Khan, N., & Babar, M. A. (2024). Innovations in precision agriculture and smart farming: Emerging technologies driving agricultural transformation. *Innovation and Emerging Technologies*, 11. <https://doi.org/10.1142/s2737599424300046>
- Adhikari, P., Mitra, J., Shovita, D. A., & Shrestha, R. (2022). UAV Multispectral Remote Sensing for Yellow Rust Mapping: Opportunities and challenges. *Open Access at Essex (University of Essex)*. <https://doi.org/10.1007/978-981>

Adhikari, P., Mitra, J., Shovita, D. A., & Shrestha, R. (2022b). UAV Multispectral Remote Sensing for Yellow Rust Mapping: Opportunities and challenges. *Open Access at Essex (University of Essex)*. <https://doi.org/10.1007/978-981>

Adhikari, P., Mitra, J., Shovita, D. A., & Shrestha, R. (2022c). UAV Multispectral Remote Sensing for Yellow Rust Mapping: Opportunities and challenges. *Open Access at Essex (University of Essex)*. <https://doi.org/10.1007/978-981>

Bhanu, A. N., Vaibhav, B., & Sanodiya, S. (2026). AI-Enabled IoT for Crop Improvement: A Paradigm Shift in Smart Agriculture. *Crop Improvement with Artificial Intelligence: Methods and Applications*, 323-357.

Awais, M., et al. (2025). Advancing Precision Agriculture Through Digital Twins and Smart Farming Technologies: A Review. *AgriEngineering*, 7(5), 137.

Rao, S., & Neethirajan, S. (2025). Computational Architectures for Precision Dairy Nutrition Digital Twins: A Technical Review and Implementation Framework. *Sensors*, 25(16), 4899.

Suthar, R. K., Parihar, R., Kumar, A., Verma, P., & Kashyap, P. (2026). Digital Twins and AI: Synergizing Intelligence for Sustainable Farm Management. Springer.

Jamba, P., & Marambi, R. (2024). Sustainable Use of Artificial Intelligent Technology: What Is It for the Global South in Achieving Inclusive Development Goals? Palgrave/Springer.

Begho, T., Daubry, P., & Irabor, J. (2025). A Scoping Review of Artificial Intelligence and the Future of African Agriculture: Opportunities, Challenges and the Path Forward. *Advances in Agriculture*, Article 2862074.

El-Sagheer, A., Ahmed, M., & Sayed, A. (2025). Social Impact of Machine Learning on Agricultural Communities. In *Machine Learning for Plant Biology*. Wiley.

Khwidzhilli, R. H., & Ijatuyi, E. J. (2026). Leveraging digital tools for sustainable precision in Agriculture 3.0–5.0: a scoping review of trends, benefits, and challenges. *Frontiers in Sustainable Food Systems*, 10, 1768902.