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From Agriculture 4.0 to Human-Centered Agriculture 5.0: Integrating AI, IoT, Robotics, Digital Twins, and Responsible Governance for Sustainable Farming

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ABSTRACT

Digital agriculture has moved beyond isolated sensing and automation toward interconnected cyber-physical systems that combine the Internet of Things, artificial intelligence, robotics, edge-cloud computing, digital twins, and human expertise. This review synthesizes 55 Scopus-indexed studies published from 2019 to 2025 to clarify how this transition is reshaping crop, livestock, aquaculture, greenhouse, and agri-food systems. Evidence was organized through qualitative synthesis of applications, architectures, performance, adoption barriers, sustainability implications, and governance requirements. Studies demonstrate task-level progress in disease recognition, weed identification, fruit counting, fertilizer recommendation, irrigation anomaly detection, robotic manipulation, and continuous livestock monitoring. Yet high model accuracy does not automatically translate into reliable farm decisions. Agricultural data remain sparse, imbalanced, heterogeneous, context-dependent, and vulnerable to sensor failure, distribution shift, weak validation, and poor interoperability. The most consequential shift in the literature is therefore conceptual: from technology-centered Agriculture 4.0 toward human-centered Agriculture 5.0, in which artificial intelligence augments rather than displaces farmers, agronomists, veterinarians, and extension professionals. This review proposes an integrated “sense–interpret–decide–act–learn–govern” framework linking field devices, multimodal analytics, decision support, autonomous intervention, feedback, cybersecurity, and accountable oversight. It also identifies six priorities for top-tier research: multi-scale sensor fusion, hybrid process–data modeling, edge intelligence, explainable and robust artificial intelligence, inclusive adoption models, and outcome-based sustainability assessment. The review concludes that the next frontier is not simply more automation, but trustworthy, interoperable, affordable, and context-aware agricultural intelligence that performs under real operational constraints while preserving farmer agency, data rights, ecological integrity, and equitable participation.

Keywords: Agriculture 5.0; human-centered artificial intelligence; digital agriculture; precision farming; smart sustainable agriculture

INTRODUCTION

Agriculture is being reorganized around data. Sensors, connected machines, aerial platforms, computer vision, machine learning, cloud services, and automated equipment increasingly mediate decisions that were once made through direct observation and accumulated experience. The central promise is compelling: measure variability more precisely, apply inputs only where needed, detect stress earlier, reduce labor bottlenecks, and coordinate production with markets. Reviews of digital agriculture describe this transition as a movement from conventional management toward a data-intensive and highly automated production system (Fountas et al., 2020; Lima et al., 2020; Javaid et al., 2022). Its scope extends beyond crop fields to livestock, aquaculture, greenhouses, postharvest quality control, machinery maintenance, and the wider food supply chain (Du et al., 2023; Kaur et al., 2023).

The first wave of this transition was framed as precision agriculture: the site-specific management of spatial and temporal variability. Agriculture 4.0 broadened that idea by integrating IoT connectivity, artificial intelligence (AI), big-data analytics, robotics, blockchain, remote sensing, and cloud computing into a common technological narrative. Smart sustainable agriculture then emphasized that digital infrastructure should serve productivity, resource efficiency, and environmental goals simultaneously (Alreshidi, 2019; Alzubi & Galyna, 2023). However, the most recent literature is no longer satisfied with cataloguing technologies. It increasingly asks whether digital systems are robust in uncontrolled environments, whether their recommendations are agronomically valid, who owns the resulting data, who can afford adoption, and whether automation increases or diminishes human agency.

This shift is visible in the emergence of Agriculture 5.0. Industry 5.0-inspired accounts retain advanced automation but reposition people, resilience, sustainability, and responsible innovation at the center of system design (Sharma et al., 2024; Holzinger et al., 2024). Human-centered AI is especially important because farms are not standardized factories. Biological processes are path-dependent; weather is volatile; soils, breeds, cultivars, and management histories differ; and the cost of an erroneous recommendation may be irreversible within a production cycle. Human expertise is therefore not simply a temporary substitute for incomplete automation. It is a source of contextual interpretation, exception handling, ethical judgment, and adaptive learning that should be explicitly designed into agricultural intelligence (Holzinger et al., 2022).

At the same time, technical capability has advanced rapidly. Deep-learning systems can classify tomato diseases with high reported accuracy, explainable models can localize downy mildew symptoms in commercial vineyards, multi-UAV systems can count fruit under variable weather, and low-cost IoT platforms can identify anomalous irrigation sensor behavior (Moussafir et al., 2022; Hernández et al., 2024; Melnychenko et al., 2024; Benameur et al., 2024). Robotic arms and field robots are progressing from single-purpose prototypes toward integrated platforms that combine perception, planning, dexterous manipulation, autonomous navigation, and cloud-edge coordination (Jin & Han, 2024; Liu et al., 2024). Digital twins are being used to represent aquaponic grow beds and greenhouse microclimates, while edge AI is proposed as a means of reducing latency, connectivity dependence, and data-transfer burdens (Reyes Yanes et al., 2022; Kavga et al., 2023; El Jarroudi et al., 2024).

These advances create a paradox. The literature contains many successful demonstrations, but adoption remains uneven and operational evidence is thinner than algorithmic evidence. Machine-learning studies often struggle with class imbalance, data sparsity, high dimensionality, leakage, and inappropriate evaluation procedures (Condran et al., 2022). Farmers report infrastructure deficits, inaccessible solutions, uncertain data quality, limited support, and weak business models (da Silveira et al., 2023a, 2023b). Digitalization can improve extension, market access, pest management, and financial inclusion, yet these gains depend on education, credit, public support, and local institutional capacity (Kitole et al., 2024). The central research problem is consequently not whether AI or IoT can perform agricultural tasks, but under what technical, agronomic, organizational, legal, and social conditions these tools create durable value.

Existing reviews generally focus on one technology, one commodity, or one application: UAVs, robotic arms, field robots, machine learning, weed management, plant disease, coffee systems, land and water management, or precision dairy farming. Their depth is useful but fragments the larger transformation. A top-tier synthesis must connect sensing to decisions, decisions to interventions, interventions to measurable outcomes, and outcomes to governance. It must also distinguish demonstrations that optimize a proxy metric from systems that improve yield stability, input efficiency, welfare, profitability, or ecological performance under real farm conditions.

This review addresses that need using a curated set of 55 publications from 2019–2025. It aims to: (1) map the technological architecture of contemporary digital agriculture; (2) synthesize evidence across crop, livestock, aquaculture, greenhouse, and agri-food applications; (3) identify why promising models fail to scale; (4) integrate sustainability, adoption, security, ethics, and regulation into one analytical framework; and (5) define a research agenda for human-centered Agriculture 5.0. The review advances the argument that the field should move from component novelty toward system-level agricultural intelligence: interoperable, explainable, robust, affordable, and governable systems that learn from biological and human feedback.

2. MATERIALS AND METHODS

The review used the two user-supplied Scopus extraction files as the exclusive evidence base. No external references were added. The dataset contained 55 journal records published between 2019 and 2025, with bibliographic metadata, abstracts, author keywords, index keywords, journal information, and digital object identifiers. The source set included broad reviews, systematic and bibliometric reviews, empirical field studies, technical system demonstrations, conceptual frameworks, governance analyses, and social-science investigations. Because the supplied material consisted primarily of abstracts and indexed metadata rather than complete articles, the synthesis was designed as a structured narrative review rather than a formal meta-analysis.

The analytical procedure had four stages. First, records were screened for relevance to digital agriculture, precision agriculture, Agriculture 4.0 or 5.0, AI, IoT, robotics, remote sensing, computer vision, digital twins, edge-cloud architectures, data governance, adoption, sustainability, or associated ethical and legal questions. All 55 records were retained because each contributed to at least one layer of the emerging agricultural intelligence system. A healthcare-focused paper on digital technologies during COVID-19 was treated only as contextual evidence regarding convergence among AI, IoT, cloud computing, big data, robotics, drones, 5G, and immersive technologies; it was not used to support agriculture-specific performance claims (Subramanian et al., 2022).

Second, each study was coded into six analytical dimensions: technological layer, agricultural domain, decision or operational function, evidence type, reported contribution, and limiting condition. Technological layers included sensing and data acquisition; connectivity and data management; analytics and AI; decision support; actuation and robotics; digital twins and simulation; and governance or human factors. Agricultural domains included field crops, orchards and vineyards, greenhouse and controlled environments, livestock, aquaculture, postharvest quality, machinery, land and water management, and supply-chain or ecosystem applications.

Third, the evidence was synthesized using a functional sequence: sense, interpret, decide, act, learn, and govern. "Sense" covers optical, environmental, positional, acoustic, biometric, and machinery data. "Interpret" includes data cleaning, feature extraction, machine learning, deep learning, and multimodal fusion. "Decide" covers recommendations, forecasts, risk classification, and control rules. "Act" includes robots, UAVs, irrigation, fertilizer application, disease or weed intervention, and environmental control. "Learn" refers to model updating, on-farm experimentation, digital twins, and feedback from outcomes. "Govern" includes cybersecurity, data rights, liability, transparency, inclusiveness, workforce development, and environmental accountability.

Fourth, the review compared reported technical performance with deployment readiness. Particular attention was given to validation context, data representativeness, interoperability, human oversight, cost, infrastructure, and whether a study reported task accuracy or downstream agricultural outcomes. Quantitative results were retained only when explicitly present in the supplied abstracts. This approach protects citation integrity: the review does not infer unreported methods or claim outcomes beyond the extracted evidence. The resulting synthesis is therefore comprehensive within the provided dataset while remaining transparent about the evidentiary limits of abstract-level source material.

3. RESULTS AND DISCUSSION

The evidence shows a field moving from digitized components toward integrated agricultural cyber-physical systems. Earlier work emphasized the enabling stack—IoT, cloud computing, big data, AI, and automation—whereas recent studies concentrate on edge intelligence, digital twins, explainable models, robotic autonomy, human-centered design, and governance. This evolution is not linear. Many farms still face basic connectivity, affordability, and skills constraints while research laboratories develop increasingly sophisticated models. The practical frontier is therefore defined by the ability to connect technological sophistication with reliability, usability, and value in heterogeneous production settings.

3.1 From Agriculture 4.0 to human-centered Agriculture 5.0

Agriculture 4.0 established the vocabulary of integration. IoT devices gather environmental and operational data; cloud platforms store and aggregate them; analytics detect patterns; and automated machines execute recommendations. In conceptual accounts, the value of IoT lies less in any single sensor than in its ability to connect other disruptive technologies and production-chain actors (Lima et al., 2020). Smart sustainable agriculture architectures similarly emphasize interoperability, data sharing, storage, and coordinated control as prerequisites for scalable platforms (Alreshidi, 2019; Alzubi & Galyna, 2023). The integrated concept proposed by Gebresenbet et al. (2023) extends this logic across data collection, platforms, AI, edge and cloud computing, blockchain, decision support, governance, and security.

Yet integration alone does not guarantee intelligence. A connected system may transmit poor-quality data faster, automate an invalid agronomic assumption, or lock users into opaque proprietary platforms. The next-generation decision-system study by Colaço et al. (2021) illustrates the importance of this distinction. A multivariate, data-driven model using vegetation, weather, soil moisture, and on-farm nitrogen-response information predicted optimum nitrogen rates more accurately than a historical-average control and then a mechanistic pathway that first predicted yield potential. The result does not imply that agronomic mechanisms are obsolete. It shows that forcing heterogeneous digital signals through a rigid intermediary model can increase decision error. Future systems must choose modeling structures according to the decision context rather than treating any one paradigm as universally superior.

Agriculture 5.0 emerges as a corrective to technology-first design. Sharma et al. (2024) link Industry 5.0, IoT, remote sensing, cognitive systems, and digital twins to sustainable and efficient farming. Holzinger et al. (2024) sharpen the concept by arguing for accessible and intuitive systems that augment farmers and maintain human oversight. This approach responds to Moravec's paradox: tasks that appear easy to experienced people—recognizing an unusual plant symptom, interpreting animal behavior, or judging whether machinery sound is abnormal—may remain difficult for AI because context is implicit and data are incomplete.

Human-centered design has operational consequences. Interfaces must communicate confidence, uncertainty, and the basis of recommendations. Systems should allow experts to correct labels, override actions, and explain local exceptions. Model-development workflows should incorporate agronomic knowledge without converting it into inflexible rules. Training and extension must treat users as co-designers rather than endpoints. Holzinger et al. (2022) define three linked frontiers: intelligent information fusion, robotics and embodied intelligence, and augmentation, explanation, and verification. These frontiers imply that trustworthy agricultural AI is not a property of an algorithm alone. It is a property of the complete human–machine system.

The literature also warns against presenting technological novelty as an unquestioned public good. Duncan et al. (2021) show that precision-agriculture discourse can privilege new tools and profit opportunities while obscuring long-standing precision-management practices and unresolved tensions over goals, adoption, uses, and impacts. Chiles et al. (2021), writing about cellular agriculture, similarly argue that fourth-industrial-revolution technologies can either intensify concentration or support democratic ownership and participation, depending on institutional design. A credible Agriculture 5.0 framework must therefore ask not only what can be automated, but who defines the problem, who benefits, who bears risk, and who retains meaningful control.

3.2 Sensing, IoT, connectivity, and data foundations

Digital agriculture begins with measurement, but agricultural sensing is unusually difficult. Devices operate under dust, moisture, vibration, temperature extremes, biological growth, animal contact, and intermittent power or connectivity. Data streams arrive at different frequencies and spatial resolutions. A camera captures visible symptoms; a soil probe samples a small volume; a weather station represents a local microclimate; a satellite integrates a much larger area. Effective systems must reconcile these scales rather than merely aggregate them.

IoT architectures provide the basic coordination layer. Smart-farming systems commonly separate sensing, networking, services, and applications. Swaminathan et al. (2023) use this architecture for an AI-enabled fertilizer recommendation delivered through a mobile application. Wei et al. (2023) combine wireless sensor networks, cloud computing, AI optimization, and big-data networks for environmental safety monitoring and report high data-reception rates in their experimental comparison. Such results show that communication reliability is measurable and should be treated as a performance variable, not an invisible assumption.

Low-cost design is particularly important for smallholders. Benameur et al. (2024) propose a fog-IoT/AI irrigation system that uses autoencoders and generative adversarial networks to identify sensor anomalies, with autoencoders reporting 90%, 95%, and 97% accuracy for soil-moisture, air-temperature, and air-humidity anomalies. The deeper contribution is architectural: anomaly detection is used to improve the quality of data before those data guide irrigation. This is essential because a smart system is only as reliable as its weakest sensor and its ability to recognize failure.

Edge computing addresses latency, bandwidth, privacy, and connectivity constraints by moving analysis closer to the field. Gupta et al. (2020) demonstrate an economical edge-AI concept for monitoring agricultural machinery health through smartphone microphones instead of expensive sensors. El Jarroudi et al. (2024) provide a broader roadmap for edge AI in sustainable agriculture, emphasizing infrastructure, training, and environmental, social, and economic constraints. Edge intelligence is especially promising for disease alerts, machinery safety, animal monitoring, and autonomous control where delayed cloud responses can reduce value or create risk.

However, edge systems introduce trade-offs. Models must fit limited memory, energy, and processing capacity. Updates may be difficult across dispersed devices. Security patches and model versions must be managed. Compression can reduce accuracy or obscure explainability. A robust architecture should therefore distribute tasks deliberately: immediate filtering, anomaly detection, and safety-critical inference at the edge; heavier training, cross-farm aggregation, and long-horizon analysis in the cloud; and clear rules for operating when networks fail.

Agricultural big data is not simply large. It is heterogeneous, sparse, seasonal, and often privately controlled. Chergui and Kechadi (2022) review data-mining applications for crop-yield management and show the expanding role of analytics in monitoring and decision support. Lassoued et al. (2021) find that experts view big-data analytics and AI as promising but stress physical investment, specialized human capital, and effective governance. These findings indicate that data value depends on institutions as much as volume. Shared standards, metadata, calibration records, provenance, and access rules determine whether data can support reusable knowledge.

Table 1. Representative digital-agriculture applications and deployment implications

Application	Data/technology	Reported contribution	Primary deployment issue	Ref.
Nitrogen decision support	NDVI, weather, soil moisture, on-farm N response	Direct multivariate prediction of optimum N rate; RMSE 16.5 kg N ha−1, R^2 0.79	Need multi-season, cross-farm validation	Colaço et al. (2021)
Irrigation anomaly detection	Soil moisture, air temperature, humidity; fog-IoT	Autoencoder accuracies of 90%, 95%, and 97% across sensor variables	Sensor drift and maintenance remain deployment risks	Benameur et al. (2024)
Vineyard disease localization	Canopy images; CNNs, ViT, XAI	Accuracy 91%, F1 0.92, localization IoU 0.83	Decision thresholds and treatment linkage required	Hernández et al. (2024)
Tomato disease classification	PlantVillage images; transfer learning ensemble	Reported accuracy 0.981	Controlled datasets may overestimate field performance	Moussafir et al. (2022)
Fruit detection and counting	Synchronized multi-UAV video; YOLOv5	mAP 86.8%; false positives 14.7%; false negatives 18.3%	Operational impact of counting bias needs assessment	Melnychenko et al. (2024)
Cocoa bean classification	Digital images; GLCM and CNN features	Handcrafted texture features more reliable on low-power device	Generalization across origins and acquisition settings	Adhitya et al. (2020)

Fertilizer recommendation	IoT four-layer architecture; deep learning; mobile app	Integrates sensor data and expert-aligned recommendation	Agronomic and economic field validation needed	Swaminathan et al. (2023)
Environmental safety monitoring	WSN, cloud, AI, big-data network	Experimental data reception remained above 95%	End-to-end reliability and field maintenance	Wei et al. (2023)
Aquaponic digital twin	pH, EC, temperature, humidity, light; virtual interface	Real-time monitoring and feedback-control framework	Biological prediction and long-term synchronization	Reyes Yanes et al. (2022)
Greenhouse digital twin and control	CFD, fuzzy logic, Arduino, LabVIEW	Simulation-guided selection and implementation of controller	Transfer across greenhouse designs and climates	Kavga et al. (2023)
Machinery health monitoring	Smartphone microphone; edge AI	Economical sensing without dedicated expensive devices	Noise robustness and device heterogeneity	Gupta et al. (2020)
Precision dairy monitoring	Sensors, actuators, networks, analytics	Continuous individual monitoring and closed-loop potential	Welfare validity, security, and interoperability	Kaur et al. (2023)
Cow facial recognition	Facial imagery; CNN/deep learning	Non-invasive identity-enabled health and behavior tracking	Breed, environment, ethics, and dataset diversity	Mahato & Neethirajan (2025)
Robotic field operations	Perception, planning, control, manipulators, mobility	Broad coverage of seeding, weeding, monitoring, harvest, protection	Sensing accuracy, operability, work rate, and cost	Jin & Han (2024); Liu et al. (2024)

3.3 Machine learning, computer vision, and explainable diagnosis

Machine learning is now embedded across agricultural tasks, but the evidence base remains methodologically uneven. Condran et al. (2022) identify class imbalance, sparsity, high dimensionality, and evaluation errors as recurring problems. These issues are acute because agricultural datasets frequently contain many healthy examples and few rare diseases, extreme events, or equipment failures. Random train-test splits can place nearly identical images, fields, seasons, or animals in both sets, producing optimistic estimates that do not represent deployment on new farms.

Computer vision illustrates both progress and risk. Fracarolli et al. (2020) describe applications from planting and disease control to robotic harvesting, postharvest grading, damage detection, and compositional analysis, including spectral regions invisible to humans. Adhitya et al. (2020) compare gray-level co-occurrence matrix features with convolutional neural-network features for cocoa-bean classification and report that handcrafted texture features were more reliable in their low-performance device context. The study is a useful reminder that deeper models are not automatically better; model choice should reflect sample size, computational budget, interpretability, and deployment conditions.

Plant-disease systems have achieved strong task-level results. Moussafir et al. (2022) evaluated multiple pretrained architectures and produced a weighted ensemble for tomato-disease identification with reported accuracy of 0.981 on the PlantVillage dataset. Hernández et al. (2024) moved closer to field reality by capturing grapevine-canopy images across commercial plots and variable lighting, using explainable AI to interpret predictions. EfficientNetV2S reached 91% classification accuracy, an F1-score of 0.92, and an intersection-over-union of 0.83 for symptom localization. The value lies not only in classification but in localization and interpretability, which can support scouting and targeted intervention.

Mahlein et al. (2024) place these advances within a larger disease-management chain: detection must lead to protection. Optical sensors, microsensor networks, robots, and AI enable site-specific responses, but implementation requires thresholds that connect symptoms to intervention decisions and regulations. A model may correctly detect a lesion without determining whether treatment is economically justified, biologically timely, or legally permitted. Future research should therefore evaluate decision consequences, not only image metrics.

Weed management faces similar requirements. Vasileiou et al. (2024) synthesize 68 studies and identify capture technology, datasets, AI models, accuracy, IoT, UAVs, field robots, and herbicide systems as interacting adoption factors. The sustainability case depends on whether detection enables meaningful reductions in herbicide use without unacceptable weed escape, crop injury, or cost. Digital literacy is also treated as an implementation factor, linking algorithm performance to workforce capability.

Explainability is necessary but should not be confused with validity. Heat maps can show where a model looked while leaving causal reasoning unresolved. Agricultural XAI should answer practical questions: which feature changed the recommendation, whether the system has seen comparable conditions, how uncertain the output is, and what evidence would justify human override. Human-centered evaluation should include agronomists' ability to detect model failure, farmers' comprehension of recommendations, and the stability of explanations under small input changes.

3.4 UAVs, robotics, and autonomous intervention

UAVs occupy a strategic position between remote sensing and action. They offer flexible spatial resolution, rapid deployment, and access to areas that are difficult to monitor from the ground. Toscano et al. (2024) review UAV architectures and applications across pest management, fertilization, irrigation, sowing, crop-health monitoring, yield forecasting, harvesting, and postharvest stages. Their assessment highlights payload, mass, battery, autonomy, cost, environmental conditions, and pilot or data-processing expertise as practical constraints.

The multi-UAV system of Melnychenko et al. (2024) demonstrates the potential of coordinated platforms. Synchronized video streams were integrated into a continuous representation for fruit detection and counting, achieving a reported mean average precision of 86.8%, with false-positive and false-negative rates of 14.7% and 18.3% under challenging conditions. The remaining errors matter operationally. Yield forecasts, labor scheduling, and harvest logistics can be distorted when detection errors are systematic across canopy density, lighting, cultivar, or weather. Multi-view fusion should therefore be evaluated not only against image annotations but against downstream planning accuracy.

Robotics converts digital interpretation into physical intervention. Jin and Han (2024) organize robotic arms around manipulators, drives, end effectors, sensors, controllers, perception, planning, and control, and survey applications in greenhouses, fields, and orchards. Liu et al. (2024) extend the discussion to field robots for tillage, seeding, weeding, monitoring, harvesting, information gathering, crop protection, and aerial operations. They identify intelligent sensing, decision and control, dexterous manipulation, stable mobility, and cloud-edge-end fusion as common enabling technologies.

Agricultural robotics differs from industrial robotics because the environment is deformable, irregular, and partially observed. Crops occlude targets; fruit vary in shape and attachment strength; soil affects traction; weather changes sensing; and safe operation may occur near people and animals. Success requires co-design among agronomy, mechanics, perception, control, and work organization. End effectors should reflect crop physiology, not merely grasping geometry. Navigation should account for soil compaction and plant damage, not only path length. Control should incorporate uncertainty and safe fallback behavior.

Smart mechanization studies also show the importance of context. Mehta et al. (2020) describe sensors, controllers, IoT, AI, robotics, GPS/GNSS, decision support, variable-rate technologies, mobile applications, and agri-bots as routes toward input savings in Indian agriculture. Goel et al. (2021) emphasize smart agriculture as an urgent need in developing countries but connect technical potential to food security, geospatial data, irrigation, and rural development. The appropriate autonomy level may therefore vary: a fully autonomous robot may suit high-value horticulture, whereas retrofit guidance, shared-service machinery, or decision-assistance may create greater value in fragmented smallholder systems.

3.5 Digital twins, simulation, and closed-loop control

Digital twins link physical assets or processes with continuously updated virtual representations. Their agricultural value lies in experimentation without immediate physical risk, prediction of future states, diagnosis of deviations, and coordinated control. Radanliev et al. (2022) position digital twins within AI-enabled IoT cyber-physical systems and emphasize interdependencies among edge components, services, human–computer interaction, and knowledge management.

Reyes Yanes et al. (2022) provide a concrete agricultural example in aquaponics. Their digital twin integrates IoT sensing, databases, centralized control, and a virtual interface to monitor pH, electrical conductivity, water temperature, relative humidity, air temperature, and light intensity, with potential AI support for growth and fresh-weight prediction. The example shows how digital twins can combine environmental and biological variables while allowing users to visualize system state and provide feedback.

Kavga et al. (2023) develop a virtual greenhouse using computational fluid dynamics in ANSYS/FLUENT and test fuzzy controllers before implementing the selected control strategy on Arduino through LabVIEW. This approach demonstrates a valuable sequence: simulate microclimate, compare control strategies, and transfer the selected logic to physical hardware. The twin is not merely a dashboard; it becomes a design and validation environment.

For digital twins to scale, models must remain synchronized with changing physical systems. Sensor drift, crop growth, equipment replacement, seasonal effects, and management changes can progressively invalidate a twin. Calibration, uncertainty quantification, and version control are therefore central. A mature agricultural twin should distinguish measured, estimated, and simulated variables; display confidence; retain provenance; and support scenario comparison without presenting predictions as certainty.

Digital twins also offer a bridge between process-based and data-driven modeling. Process models encode biological or physical knowledge but can be computationally demanding or poorly calibrated. Machine learning can approximate complex mappings but may fail outside training distributions. Hybrid twins can use mechanistic constraints to improve plausibility and data-driven residual models to capture unmodeled variation. Storm et al. (2024) identify linking process- and data-driven methods as a major research priority, alongside multi-scale sensing, improved decisions and interventions, and farmer acceptance.

3.6 Applications across crops, livestock, aquaculture, and supply chains

The application landscape reveals that digital agriculture is not one sector but a family of domain-specific systems. In crop production, the strongest evidence clusters around disease and weed detection, irrigation, fertilizer recommendation, monitoring, yield estimation, and robotic operations. Swaminathan et al. (2023) connect IoT sensing with a deep-learning fertilizer recommender. Colaço et al. (2021) show how multivariate data can support nitrogen decisions. Patel et al. (2023) map more than 60 AI techniques used in land and water management and identify neural networks, neuro-fuzzy systems, support-vector regression, random forests, and multilayer perceptrons among common methods.

Commodity-specific reviews expose different maturity patterns. Sott et al. (2020) find that IoT, machine learning, and geostatistics are prominent in coffee-sector research, but adoption challenges remain. The implication is that generic platforms must accommodate commodity calendars, quality criteria, labor structures, and local production practices. Disease detection in vineyards, cocoa-bean classification, coffee management, and orchard fruit counting require different sensors and decision horizons even when they share AI terminology.

Precision livestock farming places continuous monitoring and individualized management at the center. Kaur et al. (2023) describe multilayer networks of sensors, actuators, communication, analytics, and closed-loop management in dairy systems, with potential benefits for health, welfare, labor, environmental performance, and value-chain auditability. Mahato and Neethirajan (2025) focus on biometric facial recognition for cows as a non-invasive route to individual identification and tracking. They also identify environmental variability, breed compatibility, data collection, ethics, and technical limitations. Livestock applications demand especially careful welfare validation: a detection system should be evaluated against timely and appropriate intervention, not only identification accuracy.

Aquaculture demonstrates the ecosystem dimension of digitalization. Yang et al. (2020) analyze an AI- and IoT-based collaborative business ecosystem in Chinese fish farming, emphasizing value co-creation among participants. Digital tools can coordinate production, services, data, and markets, but the benefits depend on platform governance and the distribution of bargaining power. This echoes broader supply-chain analysis by Du et al. (2023), who show that digital technologies reshape production, transactions, retail, logistics, and consumer-facing systems.

Postharvest and food-quality applications add another layer. Computer vision can grade products, identify damage, classify categories, and analyze composition (Fracarolli et al., 2020). These systems can improve consistency and traceability, but their labels encode commercial standards that may affect producer payments. Transparency about grading criteria and calibration is therefore a governance issue, not merely a technical matter.

Large language models represent a newer application class. Kuska et al. (2024) identify potential value in preparing technical information, consulting, interpreting decision-support outputs, and producing tutorials for digital techniques. Their limitations are consequential in agriculture: language models can generate fluent but unsupported recommendations, may not reflect current local regulations, and cannot directly verify field conditions. The safest role is as an interface to validated data, models, and knowledge bases, with source tracing and expert oversight, rather than as an autonomous agronomic authority.

3.7 Sustainability performance: promise, evidence, and rebound risks

Digital agriculture is frequently justified through sustainable intensification: producing more with fewer inputs while increasing resilience. Khanna et al. (2022)

describe pathways through which site-specific technologies may reduce herbicide, nitrogen, and irrigation overuse and support cover-crop establishment in the United States. Precision systems can theoretically reduce chemical losses, water consumption, fuel use, and unnecessary field passes. Robotics may support mechanical or targeted weed control; computer vision may enable early disease intervention; and digital monitoring may improve animal health and welfare.

However, sustainability should be measured rather than assumed. Technology production, batteries, data centers, sensors, replacement cycles, and connectivity have material and energy footprints. More precise application can lower per-hectare inputs but may also encourage expansion, intensification, or increased dependence on proprietary services. Garske et al. (2021) call attention to rebound and shifting effects and argue that governance should connect digitalization explicitly to climate, biodiversity, water, and environmental-policy goals.

The appropriate evaluation unit is the complete production system. A weed-detection model should be connected to herbicide quantity, weed control, resistance management, energy use, yield, and profitability. An irrigation system should report water saved, crop response, pumping energy, and sensor-maintenance burden. A dairy-monitoring platform should assess health outcomes, welfare, labor, false alarms, and farmer workload. Technical accuracy is an intermediate metric.

Sustainability claims also vary by scale. A technology may improve resource efficiency on an adopting farm while widening regional inequality or concentrating data ownership. Conversely, digital extension and market information may improve smallholder welfare even when the technology is technically simple. Kitole et al. (2024) report that digitalization in Tanzania was associated with improvements in extension services, pest management, market information, and financial access, while adoption was influenced by credit, extension, education, and government support. These outcomes show that social infrastructure can be as important as algorithm sophistication.

An outcome-based framework should include productivity, stability under stress, input-use efficiency, greenhouse-gas implications, soil and water outcomes, biodiversity effects, labor quality, welfare, profitability, distributional equity, and farmer autonomy. Because trade-offs are inevitable, research should report who gains and over what time horizon. The goal is not to assign a single sustainability score, but to make consequences visible and comparable.

3.8 Adoption, digital divides, and workforce transformation

Adoption is often framed as a farmer's choice, but the literature shows that it is structured by infrastructure, finance, skills, service ecosystems, and institutional trust. In Southern Brazil, farmers identified lack of infrastructure, inaccessible solutions, insufficient research and development or business models, age-related risk, and unreliable rural data as major barriers (da Silveira et al., 2023b). A related framework organizes 25 barriers and uses structural modeling to identify high-driving and dependent factors, helping policymakers and developers prioritize interventions (da Silveira et al., 2023a).

These barriers interact. Poor connectivity reduces the value of cloud platforms; weak after-sales support increases downtime; uncertain returns limit credit; low digital literacy reduces effective use; and poor interoperability creates switching costs. Treating each barrier independently produces fragmented solutions. Subsidizing devices without maintenance, training, data standards, and viable service models can lead to abandonment.

Education and extension are therefore core infrastructure. Bampasidou et al. (2024) argue that higher education should develop the next generation of digital-agriculture professionals through technical upskilling, reskilling, ethical data management, and equitable change management. The needed workforce is interdisciplinary: agronomists must understand data and uncertainty; engineers must understand biological constraints; data scientists must understand sampling and causality; extension professionals must translate model outputs into locally meaningful decisions.

Business models should also match farm structure. Ownership may be appropriate for large enterprises, while smallholders may benefit from cooperatives, contractors, pay-per-use services, shared UAV operations, or public extension platforms. Open interfaces and portable data can reduce lock-in. Chiles et al. (2021) suggest that cooperatives, open-source licensing, social finance, and alternative platform models can democratize participation in advanced agricultural technologies.

Adoption research should move beyond intention surveys toward longitudinal evidence. Important questions include whether systems remain in use after pilot funding ends, how often recommendations are followed, how users adapt workflows, whether benefits persist across seasons, and how failures affect trust. Farmers' non-adoption may be rational when a system imposes hidden labor, uncertain liability, unreliable connectivity, or weak economic value.

3.9 Data governance, cybersecurity, ethics, and regulation

Farm data can reveal yields, soil conditions, input use, machinery operation, finances, animal health, and business strategy. When combined across time and space, these data become commercially and strategically sensitive. Hazrati et al. (2022) identify threats including unauthorized access, identity theft, financial loss, reputational harm, and disruption of food supply chains. Their recommendations span human-centered practices, technology controls, and physical security, showing that cybersecurity is not solved by encryption alone.

Security should be designed across the system lifecycle. Devices require secure identities and update mechanisms; networks require authentication and segmentation; platforms require access control, logging, backup, and incident response; and organizations require training and responsibility assignment. Edge AI can reduce some data transfers but increases the number of distributed assets that must be maintained. Agricultural technology providers should disclose support periods, vulnerability procedures, and data-retention practices.

Legal and ethical concerns extend beyond security. Ibrahim and Truby (2023) identify regulatory gaps affecting digital farming and propose balancing productivity opportunities with competing interests and technological complexity. Uddin et al. (2024) map concerns involving data inaccuracy, wrongful recommendations, ownership, intellectual property, privacy, security, economic division, and liability in climate-smart agriculture. They argue for national and international legal development that addresses multiple stakeholders.

Ryan (2023) organizes agricultural AI ethics around transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, autonomy, trust, dignity, sustainability, and solidarity. These principles become concrete when linked to decisions. Who is responsible when a model recommends an input rate that damages a crop? Can a farmer contest an automated grade? Are animal-monitoring systems proportionate and welfare-enhancing? Can platform providers use farm data to compete with users? Does an algorithm work equally across farm sizes, breeds, crops, languages, and regions?

Governance should be risk-based and function-specific. Low-risk advisory tools may require source transparency and uncertainty communication. Autonomous machinery requires rigorous safety validation and fail-safe behavior. Systems making financial, insurance, or market-access decisions require fairness, auditability, and appeal. Biometric livestock systems require clear purpose limitation and data controls. High-impact agricultural AI should maintain human oversight, traceable data provenance, documented validation domains, and post-deployment monitoring.

Data rights should include practical portability. Formal ownership is insufficient if farmers cannot export data in usable formats, understand permissions, or switch providers. Interoperability standards, model cards, dataset documentation, and contracts written in accessible language can reduce asymmetry. Public policy should also connect funding to open standards, cybersecurity baselines, sustainability outcomes, and inclusion rather than subsidizing technology adoption as an end in itself.

Table 2. Cross-cutting barriers and governance responses

Barrier or risk	System consequence	Priority response	Ref.
Infrastructure and connectivity	Limits cloud access, updates, and real-time coordination	Edge processing, offline modes, rural connectivity investment	da Silveira et al. (2023b); El Jarroudi et al. (2024)
Data quality and model validity	Sensor failure, sparsity, imbalance, leakage, and distribution shift	Anomaly detection, external validation, calibrated uncertainty	Condran et al. (2022); Benameur et al. (2024)
Interoperability and lock-in	Fragmented platforms reduce data reuse and switching	Open standards, portable formats, documented APIs	Alreshidi (2019); Gebresenbet et al. (2023)
Affordability and business models	High capital and support costs exclude smaller farms	Shared services, cooperatives, retrofit systems, public support	Kitole et al. (2024); Chiles et al. (2021)
Skills and digital literacy	Weakens adoption, troubleshooting, and critical use	Higher education, extension, reskilling, interdisciplinary curricula	Bampasidou et al. (2024); Vasileiou et al. (2024)
Cybersecurity	Threatens confidential data, operations, finances, and supply chains	Secure devices, access control, backups, training, incident response	Hazrati et al. (2022)
Privacy and data rights	Farmers may lose control over commercially sensitive information	Purpose limitation, consent, portability, transparent contracts	Ibrahim & Truby (2023); Uddin et al. (2024)
Liability and accountability	Wrong recommendations or autonomous actions can cause harm	Traceable decisions, human oversight, risk-based regulation	Uddin et al. (2024); Ryan (2023)
Explainability and trust	Opaque systems hinder error detection and calibrated reliance	Decision-specific explanations, confidence, override mechanisms	Holzinger et al. (2022); Hernández et al. (2024)
Environmental rebound	Efficiency gains may be offset by expansion or displaced impacts	Outcome-based assessment linked to climate, water, and biodiversity	Garske et al. (2021); Khanna et al. (2022)
Concentration of power	Platforms and data scale may favor large firms	Cooperative ownership, open licensing, public-interest governance	Duncan et al. (2021); Chiles et al. (2021)
Human agency	Automation can marginalize experiential knowledge	Human-in-the-loop design and Agriculture 5.0 principles	Holzinger et al. (2024); Sharma et al. (2024)

3.10 An integrated framework for trustworthy agricultural intelligence

The reviewed evidence supports a six-stage framework: sense, interpret, decide, act, learn, and govern. The stages are cyclical rather than sequential. Field outcomes create new data; humans correct models; and governance constrains every stage.

Sense. Data acquisition should combine fit-for-purpose sensors with calibration, metadata, redundancy, and anomaly detection. Multi-scale sensing is needed to connect plant, animal, plot, field, farm, and regional processes. Sensor quality should be monitored continuously because silent failure can be more damaging than missing data.

Interpret. Analytics should begin with data-quality checks and explicit treatment of imbalance, sparsity, missingness, and distribution shift. Model complexity should match the task and deployment hardware. Multimodal fusion should be evaluated against single-source baselines. Explanations should be designed for decisions, not only visualization.

Decide. Outputs should be expressed as actionable options with uncertainty, expected benefit, constraints, and conditions under which advice may fail. Hybrid process–data models and on-farm experimentation can improve relevance. Decision thresholds should reflect agronomy, economics, welfare, regulation, and user risk tolerance.

Act. Autonomous and semi-autonomous systems should include safe fallback modes, human override, and verification that the intended intervention occurred. Robotic performance should be evaluated under representative field variability and against crop damage, soil effects, energy use, and work-rate requirements.

Learn. Digital twins, longitudinal monitoring, and outcome feedback should update both models and management practices. Systems should detect drift and trigger recalibration. Learning should occur across farms without requiring uncontrolled extraction of sensitive data; privacy-preserving or federated approaches are promising, although they were not directly evaluated in the supplied studies.

Govern. Data rights, cybersecurity, accountability, accessibility, workforce capability, and environmental outcomes must be specified at design time. Governance is not an administrative layer added after deployment. It determines which data are collected, what objectives are optimized, whose values are represented, and how errors are corrected.

Within this framework, system maturity can be assessed at four levels. Level 1 is observability: reliable sensing and visualization. Level 2 is advisory intelligence: validated predictions and recommendations with human decisions. Level 3 is supervised autonomy: automated intervention with monitoring and override. Level 4 is adaptive, accountable autonomy: closed-loop action, drift detection, transparent governance, and verified sustainability outcomes. Many published demonstrations remain between Levels 1 and 2 even when their algorithms are advanced. This distinction can prevent inflated claims and guide realistic development pathways.

3.11 Research agenda

First, the field needs multi-scale, multi-sensor datasets designed around agricultural decisions rather than convenient data collection. Storm et al. (2024) identify this as a central priority. Datasets should span seasons, locations, genotypes, management regimes, devices, and rare adverse events. Shared benchmarks should protect sensitive data while enabling reproducibility.

Second, comparative modeling must be more rigorous. Patel et al. (2023) recommend comparative evaluation of AI techniques for specific land- and water-management domains. Agricultural studies should use spatial, temporal, farm-level, or animal-level holdouts; report calibration and uncertainty; and evaluate simpler baselines. External validation should be expected for claims of general applicability.

Third, hybrid intelligence should connect process knowledge, data-driven models, and human expertise. The objective is not to choose between mechanistic and machine learning approaches, but to determine which combination improves decisions under uncertainty. On-farm experiments, causal inference, and digital twins can help separate correlation from management response.

Fourth, edge-cloud architectures need life-cycle evaluation. Research should report latency, energy use, connectivity requirements, update processes, security, device cost, and maintenance, not only inference accuracy. Edge AI has strong potential, but its sustainability and usability depend on durable hardware and support systems.

Fifth, explainability should become task-specific. The field needs evidence that explanations improve error detection, trust calibration, and decisions. Explanations that increase confidence without improving understanding can be harmful. Human-centered trials should compare interface designs and measure how users respond to uncertainty and conflicting evidence.

Sixth, autonomous systems require safety and operational benchmarks. Robotic arms, field robots, UAVs, and control systems should be tested across realistic weather, terrain, crop variability, occlusion, and human proximity. Standard metrics should include intervention success, damage, work rate, downtime, energy, recovery from failure, and total cost.

Seventh, adoption research should integrate economics, behavior, institutions, and distributional outcomes. Khanna et al. (2022) highlight economic factors, farmer preferences, social networks, and ex ante adoption assessment. Future work should examine service models, financing, insurance, procurement, extension, and the persistence of use after pilots.

Eighth, legal and ethical design should be embedded in technical projects. Data governance, liability, privacy, intellectual property, contestability, and labor implications should be specified before data collection. Regulatory sandboxes and participatory governance can allow innovation while making risks visible.

Ninth, sustainability evaluation should move from proxy claims to measured outcomes. Digital tools should be compared with credible non-digital alternatives and assessed for rebound effects. Studies should report environmental and social costs of the technology itself, including energy, hardware turnover, and dependence on external platforms.

Tenth, large language models should be integrated cautiously. Agricultural LLMs should retrieve from validated, localized sources; cite evidence; expose uncertainty; and route high-risk recommendations to experts. Their strongest near-term role is likely translation, documentation, training, and explanation of validated decision-support systems, as suggested by Kuska et al. (2024), rather than unsupervised crop or animal management.

Finally, review practice itself should become more cumulative. Technology-centered reviews frequently classify devices or algorithms but use incompatible taxonomies, making it difficult to compare maturity across domains. Future reviews should code the full evidence chain: data provenance, validation unit, decision target, intervention mechanism, operational setting, outcome metric, adoption model, and governance safeguards. They should also distinguish evidence derived from controlled datasets, field pilots, commercial operations, stakeholder perceptions, and legal or conceptual analysis. This common structure would make updates more efficient and prevent repeated claims of novelty when the unresolved issue is implementation. Living evidence maps could track which crops, regions, farm scales, and sustainability outcomes are represented and where knowledge is absent. Because digital agriculture changes quickly, synthesis should also record software and hardware dependencies, data availability, and whether systems remain supported. A cumulative evidence infrastructure would help researchers select meaningful baselines, allow policymakers to identify mature versus speculative applications, and enable practitioners to judge whether reported results resemble their operating conditions. In this way, literature reviews can function not only as summaries of technological activity, but as governance instruments that improve transparency, research prioritization, and responsible translation.

3.12 Evidence quality, benchmarking, and translation to farm outcomes

The supplied literature demonstrates substantial technical momentum, but it also reveals a persistent mismatch between the unit of algorithm evaluation and the unit of agricultural value. Most AI systems are evaluated on images, sensor readings, or predicted labels. Farmers, in contrast, experience consequences at the level of fields, herds, harvests, input bills, labor schedules, and risk exposure. A classifier can improve image accuracy without improving disease control if it detects symptoms too late, produces excessive false alarms, or cannot be connected to a feasible intervention. A yield estimator can reduce statistical error without improving profit if the estimate arrives after marketing or input decisions have been made. Translation therefore requires a chain of evidence from data quality to model validity, decision usefulness, intervention fidelity, and measurable outcomes.

The first benchmarking problem is representativeness. Agricultural datasets are shaped by season, geography, cultivar, breed, soil, management, camera, sensor model, and labeling protocol. A random sample from one pooled dataset rarely tests the ability to perform in a new production context. Condran et al. (2022) show why agricultural machine learning requires special attention to sparsity, imbalance, dimensionality, and evaluation design. These concerns should lead to hierarchical validation: within-site testing for development, leave-one-field or leave-one-farm-out testing for spatial transfer, leave-one-season-out testing for temporal transfer, and external testing for claims of broad generalization. For livestock biometrics, the analogous unit is the animal, farm, breed, or housing system. For machinery monitoring, it is the machine type, operating state, microphone, and acoustic environment.

The second problem is benchmark relevance. Public image datasets accelerate method development, but controlled backgrounds and balanced classes may not reflect occlusion, mixed symptoms, varying growth stages, or operator motion. The strong tomato-disease result reported by Moussafir et al. (2022) is valuable as a model-development result, while the commercial-vineyard study of Hernández et al. (2024) offers a complementary form of evidence because it includes field lighting and on-the-go acquisition. These studies should not be ranked solely by accuracy; they answer different questions. A mature review distinguishes laboratory discrimination, field recognition, decision support, and operational impact as separate readiness stages.

The third problem is comparison. Agricultural AI papers often compare several modern architectures while omitting simple baselines, expert performance, or existing farm practice. The cocoa-bean study by Adhitya et al. (2020) is instructive because a conventional texture representation outperformed CNN-based feature extraction in its low-compute implementation. This result supports a general principle: the best model is the one that provides the required reliability, speed, cost, and interpretability in the intended environment. Benchmarking should include persistence models, threshold rules, conventional statistics, mechanistic models, and human judgment when these are realistic alternatives.

The fourth problem is calibration. A model that is correct 90% of the time can still be unsafe if it is overconfident on the 10% of cases it gets wrong. Decision systems need calibrated probabilities, uncertainty intervals, and out-of-distribution warnings. These are particularly important for rare pests, disease outbreaks, extreme weather, and equipment faults, where the data are sparse but the stakes are high. Explanations should be paired with confidence and evidence of similarity to the training domain. Without that context, visually persuasive explanations may create unwarranted trust.

The fifth problem is intervention fidelity. When a recommendation is executed by a person, robot, UAV, valve, or variable-rate applicator, the delivered action may differ from the intended action. Robotics reviews identify manipulation, mobility, sensing, control, and work-rate limitations (Jin & Han, 2024; Liu et al., 2024). Evaluation should therefore measure whether the system reached the correct target, delivered the correct dose or physical action, avoided damage, and recovered from failure. In controlled environments, digital twins can support pre-deployment testing, but their predictions must be validated against physical outcomes (Reyes Yanes et al., 2022; Kavga et al., 2023).

The sixth problem is economic and ecological attribution. A before-and-after improvement may reflect weather, prices, management attention, or selection of motivated pilot farms. Stronger designs include randomized or phased rollouts, matched comparisons, on-farm strips, repeated seasons, and sensitivity analysis. Colaço et al. (2021) demonstrate the value of long-term experimental context and an explicit control scenario in nitrogen decision support. Similar rigor is needed for claims about water savings, pesticide reduction, labor substitution, animal welfare, and profitability.

The seventh problem is reporting. Top-tier digital-agriculture studies should document the data-generating process, missingness, label quality, preprocessing, split strategy, hyperparameter selection, hardware, latency, power use, connectivity, maintenance, and failure cases. They should state the population and environments to which results plausibly apply. For deployable systems, reporting should also include user workflow, decision timing, cost structure, update policy, cybersecurity controls, and the handling of uncertainty. This expanded reporting burden is justified because the object of evaluation is a sociotechnical system, not only a predictive function.

A practical evidence ladder can help organize future reviews. Level A evidence establishes technical feasibility in controlled data. Level B establishes external or field validity. Level C shows decision utility compared with existing practice. Level D demonstrates intervention effectiveness and operational reliability. Level E documents multi-season economic, environmental, welfare, or social outcomes. Level F demonstrates transferability, governance, and sustained adoption across diverse users. Current literature is rich at Levels A and B, growing at C and D, and comparatively limited at E and F. Recognizing this distribution does not diminish technical achievements; it clarifies the next research task.

3.13 System orchestration, resilience, and failure-aware design

As digital agriculture becomes integrated, failure no longer occurs only within individual components. A sensor may drift, a network may disconnect, a cloud service may become unavailable, an AI model may encounter unfamiliar conditions, a robot may fail to grasp, or a user may misunderstand an alert. These failures can interact. A moisture sensor that slowly drifts may trigger a confident irrigation recommendation; a connectivity outage may prevent an update; and an automated controller may execute the wrong action repeatedly. System orchestration must therefore be failure-aware.

Resilience begins with graceful degradation. A farm platform should define what happens when each dependency is unavailable. Edge processing can maintain essential functions during disconnection, while cloud services can support heavier analytics and cross-site learning when communication is restored. El Jarroudi et al. (2024) emphasize edge AI as a route to sustainable, responsive agricultural systems, while Gupta et al. (2020) show how economical sensing and local computation can reduce dependence on specialized infrastructure. The design objective is not to move all computation to the edge, but to allocate functions according to latency, risk, privacy, energy, and maintainability.

Redundancy should be selective. Duplicate sensors can increase cost and maintenance, but cross-checking among different modalities can detect implausible states. Soil-moisture readings can be checked against irrigation events, rainfall, and evapotranspiration; machine acoustics can be compared with vibration or operating load; animal identity can be checked against location and milking records. Benameur et al. (2024) show how learned anomaly detection can identify and reconstruct suspect sensor values. Such reconstruction should be labeled and logged so estimated data are not silently treated as observations.

Resilience also requires explicit operating envelopes. Models and autonomous systems should declare the conditions under which they were validated: temperature range, illumination, crop stage, field slope, wind speed, network latency, breed, or device configuration. When conditions fall outside these boundaries, systems should reduce autonomy, request human review, or revert to safe control rules. This approach aligns with human-centered AI because it uses people strategically where machine confidence and domain coverage are insufficient.

Digital twins can serve as resilience tools by simulating disturbances, component failures, and alternative controls before deployment. Radanliev et al. (2022) frame the digital twin as a real-time counterpart within interconnected cyber-physical systems. In agriculture, a useful twin should support stress testing: loss of a sensor, extreme heat, delayed irrigation, disease spread, equipment degradation, or a sudden change in energy availability. Scenario analysis can reveal single points of failure and help design fallback policies.

Cybersecurity and operational resilience are inseparable. A malicious command and a faulty command may produce the same physical harm. Hazrati et al. (2022) emphasize human, technological, and physical safeguards, while Wei et al. (2023) focus on reliable agricultural data transmission. Authentication, access control, secure updates, logging, and incident response protect both confidentiality and physical operations. Because many farms lack dedicated IT staff, security controls must be usable, supported, and proportionate to risk.

Organizational resilience depends on service arrangements. A technologically advanced system can fail commercially if replacement parts, calibration, connectivity, or technical support are unavailable. Farmers need clear service-level expectations, ownership of historical data, and procedures for continuing operations if a provider exits the market. Interoperable components and exportable data reduce dependence on any single vendor. The integrated architecture of Gebresenbet et al. (2023) is strongest when interpreted not as a fixed platform but as a modular ecosystem with governance and security built into each interface.

Resilience also changes the meaning of optimization. A system optimized for average yield may be fragile under drought, disease, or market disruption. Agriculture 5.0 should optimize robustness and recoverability alongside efficiency. This may favor diversified sensing, conservative thresholds, human review, buffer capacity, and local knowledge, even when those choices reduce short-term algorithmic efficiency. The agricultural intelligence model proposed by S.S. et al. (2024) links technology to self-sustained growth and economic stability; resilience metrics are needed to make that ambition testable.

A failure-aware design process should include hazard analysis, field stress tests, red-team exercises for data and security, and post-deployment monitoring. Developers should publish known failure modes and update them as evidence accumulates. Users should be able to report anomalies and see whether corrective action has been taken. Regulators and insurers can encourage these practices through safety standards and incentives. The result is a shift from systems that perform impressively when everything works to systems that remain useful and safe when parts of the system do not.

3.14 Regional pathways and differentiated strategies for scale

Digital-agriculture strategies should not assume a universal farm, infrastructure base, or adoption pathway. The reviewed studies span the United States, Brazil, Tanzania, India, China, Europe, and globally framed systems. Their differences show why scale must be understood as adaptation across contexts rather than replication of one technological package.

In capital-intensive production systems, digitalization may focus on integrating existing machinery, dense sensing, autonomous operations, and farm-management platforms. Khanna et al. (2022) discuss site-specific technologies in relation to herbicide resistance, nitrogen and irrigation efficiency, cover crops, farmer behavior, and social networks in the United States. Here, adoption decisions may turn on compatibility with equipment, return on investment, data contracts, and evidence that environmental gains persist at commercial scale.

In developing-country contexts, infrastructure, finance, extension, and service availability often dominate. Kitole et al. (2024) show that credit, education, extension, and government support influence adoption and that digitalization can improve market, pest-management, extension, and financial access. Goel et al. (2021) connect smart agriculture with food security, rural development, geospatial information, irrigation, and the economic importance of agriculture. These findings support staged strategies: strengthen connectivity and digital extension; prioritize low-cost, high-value decisions; support shared services; and build local repair and training capacity before promoting fully integrated autonomy.

Brazilian evidence provides a detailed barrier perspective. da Silveira et al. (2023b) validate farmers' concerns about infrastructure, accessible solutions, business models, age-related risks, and rural-data efficacy. Their companion framework identifies structural relationships among barriers (da Silveira et al., 2023a). This suggests that policy should target high-driving barriers rather than distribute isolated subsidies. Connectivity, trusted support, standards, finance, and relevant research can unlock multiple downstream improvements.

India's mechanization context also emphasizes differentiated pathways. Mehta et al. (2020) describe smart machinery, precision irrigation, mobile applications, GPS/GNSS, variable-rate technology, and robotics as a portfolio rather than a single endpoint. Retrofit systems and mobile decision support may generate immediate benefits where machinery fleets are diverse and farm sizes vary. Shared equipment and custom-hiring centers can distribute capital costs, but require scheduling, maintenance, and transparent pricing.

Platform ecosystems matter in aquaculture and supply chains. Yang et al. (2020) show how AI and IoT can support value co-creation in a Chinese fish-farming ecosystem. Yet platform design determines who captures data value and who can participate. Regional strategies should consider cooperatives, public digital infrastructure, interoperability mandates, and competition policy so that network effects do not produce excessive dependency.

Europe's policy discussion links digitalization with climate, biodiversity, privacy, product safety, and the Common Agricultural Policy. Garske et al. (2021) argue that governance has not fully connected digital innovation to environmental objectives and may overlook negative side effects. Uddin et al. (2024) and Ibrahim and Truby (2023) similarly emphasize legal gaps, liability, privacy, and multi-stakeholder interests. These concerns are relevant globally, but regulatory capacity and enforcement vary. International principles should therefore be translated into implementable national and sectoral rules.

Regional differentiation should also apply to research infrastructure. Benchmark datasets dominated by a few countries or crops will produce models that travel poorly. Local institutions should participate in dataset design, labeling, validation, and governance. Capacity building must include the ability to audit imported systems and to develop locally relevant alternatives. Bampasidou et al. (2024) position universities and extension programs as critical to closing these skills gaps.

A scalable strategy can be organized around four pathways. The foundational pathway provides connectivity, identifiers, basic records, and decision-support access. The augmentation pathway adds low-cost sensing, mobile analytics, and human-centered recommendations. The supervised-automation pathway connects validated decisions to machinery, irrigation, greenhouse control, or livestock systems with human oversight. The adaptive-autonomy pathway adds digital twins, continuous learning, and advanced robotics where economics, skills, safety, and governance permit. Regions and sectors can occupy different pathways simultaneously.

This differentiated model avoids two errors. The first is technological leapfrogging as rhetoric: assuming that advanced AI can bypass weak infrastructure and institutions. The second is technological minimalism: assuming that smallholders or developing regions should receive only simplified tools. The correct principle is proportional sophistication—systems as advanced as necessary, but affordable, maintainable, locally governable, and matched to the decision value. Agriculture 5.0 should expand capability without creating new forms of exclusion.

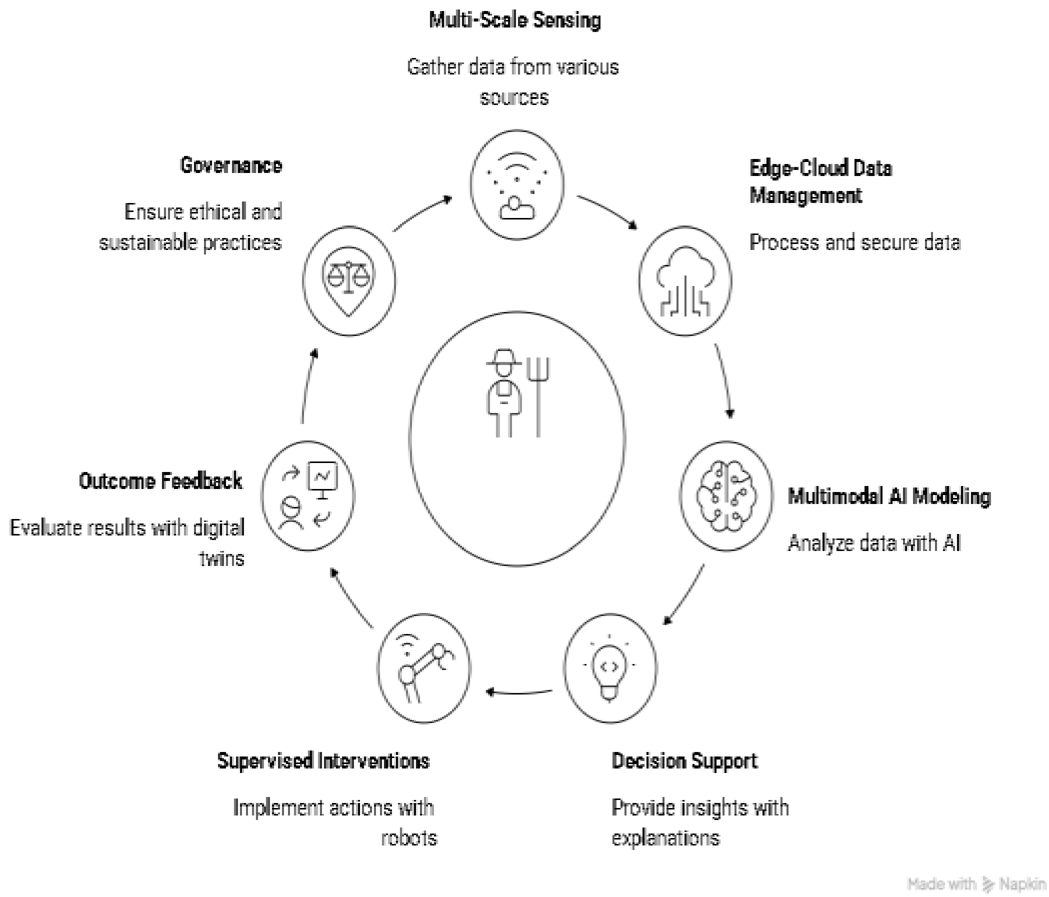

Figure 11. Agriculture 5.0 Cycle

Figure 1. A human-centered Agriculture 5.0 architecture organized as a closed loop: (1) multi-scale sensing from soil, crop, animal, machinery, weather, UAV, and market

sources; (2) edge–cloud data management with interoperability, provenance, anomaly detection, and cybersecurity; (3) multimodal AI and hybrid process–data modeling; (4) decision support communicating uncertainty and explanations; (5) supervised robotic, irrigation, input, greenhouse, and livestock interventions; (6) outcome feedback through digital twins and on-farm learning; and (7) an outer governance ring covering farmer agency, data rights, safety, liability, inclusion, and sustainability metrics. The figure should visually distinguish the operational loop from the governance layer and show the farmer/domain expert at the center rather than outside the system.

CONCLUSION

Digital agriculture is entering a system-integration phase. The literature no longer supports a simple narrative in which more sensors, larger datasets, and more complex algorithms automatically produce sustainable farming. Strong technical progress is evident in computer vision, disease localization, irrigation anomaly detection, fertilizer recommendations, UAV-based fruit counting, robotics, livestock biometrics, edge AI, and digital twins. Yet operational value depends on data quality, validation, interoperability, cost, infrastructure, human capability, and governance.

The defining transition is from Agriculture 4.0 to Agriculture 5.0. Agriculture 4.0 connected devices, data, and automation. Agriculture 5.0 must connect those capabilities to human judgment, resilience, sustainability, and accountability. Farmers and domain experts should remain active participants who frame objectives, interpret uncertainty, correct errors, and retain authority over high-consequence actions.

The proposed sense–interpret–decide–act–learn–govern framework provides a way to evaluate complete agricultural intelligence systems rather than isolated algorithms. It also reveals where evidence is missing. Many studies report accuracy, but fewer demonstrate durable improvements in input efficiency, yield stability, animal welfare, profitability, biodiversity, or equity under real farm conditions.

The next generation of research should prioritize representative multi-season datasets, hybrid process–data models, robust edge-cloud systems, decision-oriented explainability, safe autonomy, inclusive service models, and enforceable data governance. Progress should be judged by dependable performance under biological and environmental variability and by the distribution of benefits and risks. The most valuable agricultural AI will not be the system that removes people from farming. It will be the system that makes expert knowledge more effective, expands access to reliable decisions, protects data and autonomy, and enables measurable ecological and economic improvement.

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