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Review

Technical Limitations and Research Gaps of IoT and Big Data Infrastructures in Precision Crop Production: A Design-Oriented Review

Anikó Nyéki

Department of Bioengineering and Precision Technology, Albert Kázmér Mosonmagyaróvár Faculty of Agricultural and Food Sciences, Széchenyi István University, 9200 Mosonmagyaróvár, Hungary; nyeki.aniko@sze.hu

Abstract

Precision crop production increasingly relies on Internet of Things (IoT) devices, heterogeneous sensor networks, machine telemetry, and data-intensive analytics to monitor field conditions, support decisions, and enable variable-rate or autonomous operations. However, farm-scale multi-season adoption remains limited by technical constraints that are often reported only as general challenges. This design-oriented review clarifies those constraints at the infrastructure level. It is not a quantitative meta-analysis; rather, it combines a transparent multi-database search, a PRISMA-type selection record and thematic design synthesis of the 2020–2025 literature, supplemented by selected 2026 studies and current interoperability and security specifications. The review addresses four research questions covering field hardware and connectivity failures, edge-to-cloud data management, integration with farm management information systems and agricultural machinery, and future design priorities. The synthesis identifies recurring gaps in multi-season reliability evidence, calibration and self-diagnostics, energy and connectivity benchmarking, operational definitions of agricultural Big Data, metadata/FAIR implementation, ISO 11783/ISOBUS–FMIS interoperability, lightweight cybersecurity, and serviceability. The main outputs are an evidence-traceability matrix, a distributed reference architecture specifying inputs, outputs, standards, validation points and edge/cloud placement, an operationalized G1–G10 gap matrix with indicators and evaluation designs, and minimum reporting requirements for future agricultural IoT studies. These outputs are intended to make field systems more interoperable, maintainable, secure, and evaluable. Because the corpus combines heterogeneous evidence types and does not support quantitative meta-analysis, the outputs should be interpreted as design and reporting guidance rather than comparative performance estimates.

Keywords: precision crop production; Internet of Things (IoT); big data analytics; sensor networks; compatibility; security

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1. Introduction

Precision crop production has shifted from GNSS-guided variable-rate application toward digitally connected production systems that combine in-field sensors, machine telemetry, communication networks, edge and cloud computing, and data-driven decision support [1–3]. In this transition, IoT platforms and Big Data infrastructures function as the technical backbone that links sensors, actuators, gateways, agricultural machinery, farm management information systems (FMIS), and cloud services into multi-layer architectures. Their expected value is not only more precise input management, but also earlier stress detection, more transparent operations, and shorter sensing-to-control loops.

At the same time, the adoption of this technology is proceeding more slowly than the optimistic findings of numerous studies suggest. Recent reviews have repeatedly pointed to unreliable hardware in field conditions, limited internet access in rural areas, fragmented standards, high acquisition and maintenance costs, and continuing barriers to digital competence as practical constraints to adoption at the farm level [4–7]. These constraints have particularly significant implications for field crop production, where large spatial scales, mobile machinery, extreme weather, and narrow operational windows further amplify the technical limitations.

A further limitation of the literature is that, although application-oriented surveys are abundant, far fewer reviews explain where and why current systems fail at the technical level. Recent reviews provide useful overviews of IoT applications and smart-environment taxonomies [8,9], while other reviews focus specifically on edge computing or cybersecurity [10,11]. However, the technical weak points of open-field crop-production systems are rarely placed at the center of the analysis. For developers of agricultural machinery, gateways, farm-management platforms, and multi-vendor digital infrastructures, this leaves important questions about reliability, latency, interoperability, serviceability, and security insufficiently resolved.

Recent forward-looking reviews of precision and sustainable agriculture [12,13] confirm the expansion of IoT-based crop-production research, but they also show that infrastructure failure modes are often treated only as secondary constraints within application-oriented narratives. This creates a need for a more focused review that evaluates implementability, maintainability, and interoperability across infrastructure layers.

This emphasis on system-level constraints is supported by earlier literature. Zhai et al. [14] linked the maturity of Agriculture 4.0 to decision-support systems and platform integration, while Villa-Henriksen et al. [15] showed that arable farming requires a more complex IoT environment than most generic smart-farming overviews suggest because of mobile machinery, spatial variability, and field logistics. Saini et al. [16] similarly framed IoT and emerging data analytics as an integrated precision-agriculture system while highlighting persistent infrastructure, cost, integration, and security concerns.

The farm-management and software-architecture literature reinforces this point from the perspective of compatibility. In practice, digital agriculture depends not only on ad hoc point-to-point integration, but also on well-defined reference architectures, reusable ecosystem models, and model-driven approaches to configuration [17–21].

The pioneering studies on wireless sensor networks in agriculture, the Internet of Things (IoT) and Big Data have highlighted the importance of energy-efficient sensing, interoperable communication, data management, and decision-oriented analysis [22–30]. Moreover, recent studies on smart farms and FMIS architectures have shown that reliable operation requires integrated models, open service interfaces, local availability during network failure, management systems, and control functions [31–36]. These requirements continue to be relevant, as newer wireless technologies and data analysis methods cannot, on their merits alone, resolve issues of cross-layer integration or service sustainability.

This review makes four specific contributions relative to previous application-oriented surveys. First, it frames the review explicitly as a design-oriented synthesis of infrastructure limitations rather than as a catalogue of crop applications. Second, it distinguishes evidence types—field empirical studies, previous reviews, normative standards, conceptual proposals, and architecture studies—so that the weight of conclusions is traceable. Third, it operationalizes the G1–G10 gap matrix by linking each gap to measurable indicators, example metrics, evaluation designs, and priority level. Fourth, it proposes a reference architecture and minimum reporting requirements that future agricultural IoT studies can use to document deployment duration, energy budget, gateway layout, latency, packet loss, calibration, metadata, traceability, update mechanisms, and security controls.

This study is organized around four research questions that are answered explicitly in Section 3:

RQ1. *What technological limitations and failure modes affect IoT hardware, sensor networks and communication systems under open-field crop-production conditions?*

RQ2. *How do edge-to-cloud data architectures affect reliability, latency, traceability, scalability, and quality?*

RQ3. *Where do interoperability challenges emerge between IoT platforms, FMIS, ISOBUS/ISO 11783 [37] machinery, and open information models?*

RQ4. *Which design challenges related to compatibility, scalability, cybersecurity, power supply, serviceability, and cost should be prioritized in future research and reporting?*

2. Materials and Methods

2.1. Review Structure and Scope

This manuscript is a design-oriented integrative review. PRISMA 2020 terminology is used only to improve transparency in record identification, screening, and exclusion reporting; the study does not estimate pooled effect sizes and is not presented as a formal quantitative meta-analysis [38]. The scope of the study is limited to IoT and Big Data infrastructures for open-field crop production, including sensors and actuators, communication networks, gateways and edge nodes, data pipelines, interoperability models, machinery, FMIS interfaces, cybersecurity, and data-ownership mechanisms that directly affect field decision support or machine control.

The selection criterion was relevance from a technical design perspective. Sources were considered if they contained evidence, standards, architectures, or sufficiently detailed studies that could contribute to the scalability, serviceability, compatibility, security, or reliability of agricultural IoT systems. Case studies were included only if the infrastructure making them possible was described in enough detail to support coding.

The core period covered by the review was January 2020–December 2025. Selected 2026 publications were added when they provided direct system-level value, such as updated edge-computing reviews, cybersecurity mechanisms or firmware updates, and serviceability evidence. Foundational standards and older landmark studies were retained when necessary for conceptual continuity, for example, ISO 11783/ISOBUS, OPC UA, OGC SensorThings API, ISO 19156/observations, measurements, and samples (OMS), and SOSA/SSN semantics.

2.2. Sources and Search Strategy

The database search yielded 657 records: Scopus (n = 182), Web of Science Core Collection (n = 136), IEEE Xplore (n = 91), ACM Digital Library (n = 48), and the first 200 results ranked as relevant by Google Scholar (n = 200). A further 59 records were identified from official standards and specification sources (n = 17) and manual citation searches (n = 42). Google Scholar was used as a complementary source rather than as a fully reproducible bibliographic database. The search flow and exclusion counts are reported in Figure 1.

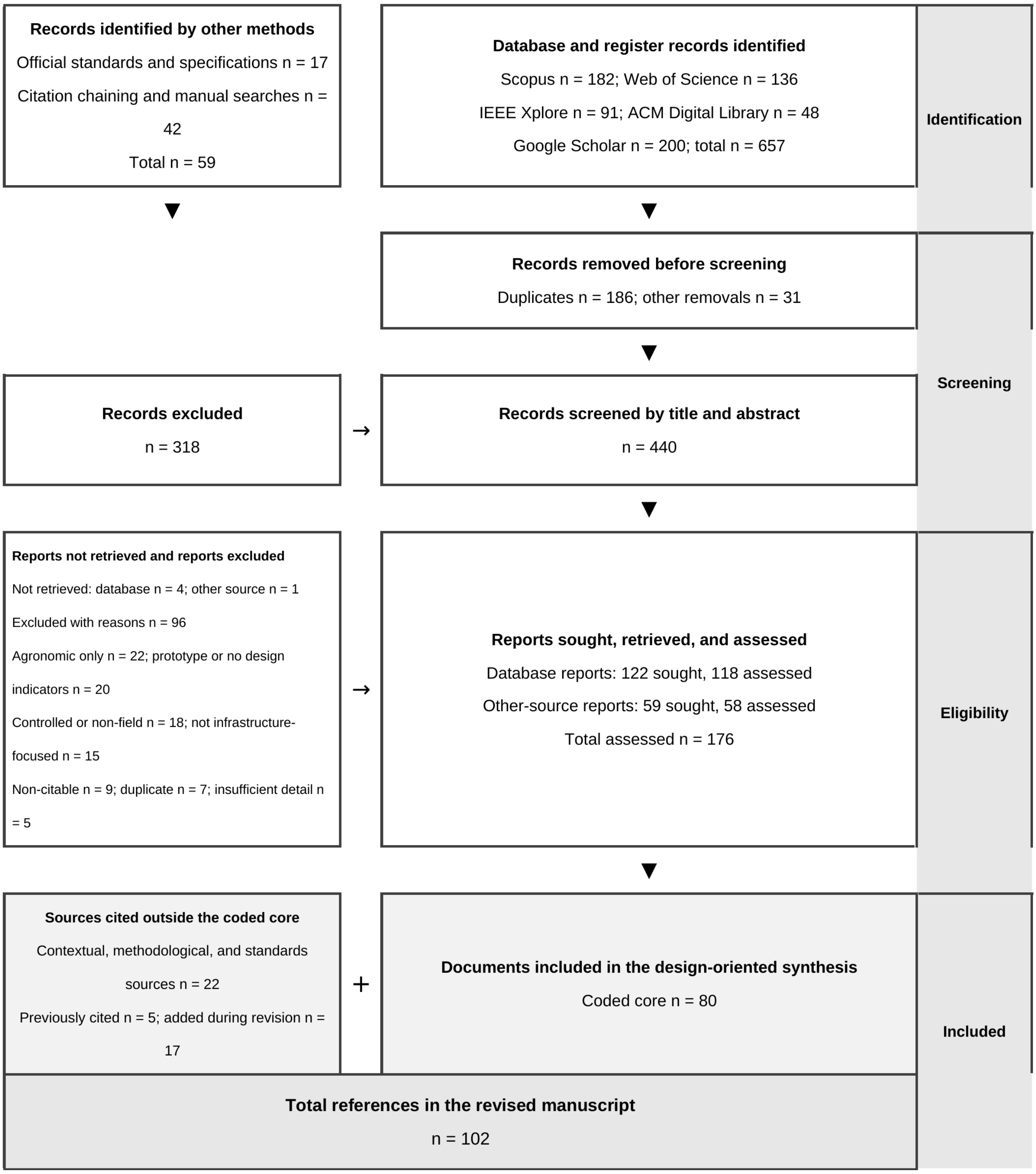

Figure 1. PRISMA 2020-style bibliographic selection flow diagram for the design-oriented review. The editable diagram distinguishes the coded 80-document synthesis corpus from 22 contextual, methodological, and standards sources cited outside the coded core, giving 102 references in the revised manuscript.

The generic search equation was as follows: (“precision agriculture” OR “precision crop production” OR “smart farming” OR “field crops” OR “open-field”) AND (“Internet of Things” OR IoT OR “wireless sensor network” OR LoRaWAN OR LPWAN OR NB-IoT OR 5G OR “edge computing” OR “cloud platform” OR “big data” OR FMIS OR ISOBUS OR “ISO 11783” OR “OPC UA”) AND (limitation* OR challenge* OR bottleneck* OR reliability OR calibration OR drift OR energy OR latency OR security OR privacy OR interoperability OR metadata OR FAIR OR scalability OR maintainability). A standards-specific query combined (“SensorThings” OR “ISO 19156” OR SOSA OR SSN OR “NGSI-LD” OR MQTT

OR LwM2M OR ADAPT) with agriculture/farm/machinery terms. Database syntax was adapted to each platform, but the conceptual blocks were kept constant.

The bibliographic search was complemented by official standards and reference architecture sources because agricultural interoperability is often specified outside journal articles. This included OGC SensorThings API, ISO 19156/observations, measurements, and samples, ETSI NGSI-LD, OASIS MQTT 5.0, OMA LwM2M, AgGateway ADAPT, and NIST IoT cybersecurity guidance [39–47]. These sources were coded as normative or implementation specifications rather than empirical evidence.

2.3. Eligibility Criteria and Screening

Eligibility criteria were defined before thematic coding. Sources were included when they (i) addressed IoT, sensor-network, communication, edge/cloud, FMIS, ISOBUS/ISO 11783, interoperability, cybersecurity, or Big Data infrastructure aspects of agricultural production systems; (ii) discussed a technical constraint, failure mode, bottleneck, metric, or design pattern rather than merely mentioning "IoT" or "Big Data"; and (iii) provided sufficient implementation detail for layer, evidence type, research-question, and gap coding. Exclusion criteria were purely agronomic outcome studies without infrastructure detail, generic non-agricultural IoT articles, opinion pieces without technical content, duplicate records, and controlled-environment or livestock-only studies unless the technical principle was transferable to open-field crop production.

The screening process took place in two stages: first, a review of the titles and abstracts, followed by an analysis of the full texts to determine their relevance. Of the 657 items from the databases and the additional 59 records, 186 duplicates and 31 items that could not be screened or were definitely irrelevant were excluded before the screening began. A total of 440 records were reviewed based on title and abstract, and 318 were excluded. The full text of 122 database records and 59 records from other sources was retrieved; 4 database reports and 1 report from another source were not available. A total of 176 reports were reviewed for eligibility, and 96 were rejected with reasons. The final, design-oriented synthesis included 80 documents (Figure 1).

The 17 sources added during revision [22–36,48,49] were used for historical context and recent illustration and were not added retrospectively to the coded 80-document core corpus. Together with five methodological or standards references already cited outside the synthesis corpus [38,40,45–47], they bring the number of sources outside the coded core to 22 and the complete reference list to 102.

The 96 excluded full-text documents were coded as follows: solely agronomic focus, lacking details on technical infrastructure (n = 22), articles on prototypes or applications, without implementation indicators or design limitations (n = 20), studies conducted in controlled environments, in animal husbandry or under non-field conditions, lacking scalable infrastructure evidence (n = 18), sources not focused on IoT, Big Data, interoperability, or security infrastructure (n = 15), opinion pieces, marketing materials, or non-citable materials lacking technical specifications (n = 9), duplicated or overlapped records (n = 7), and insufficient methodological or systemic details (n = 5).

2.4. Data Extraction and Synthesis Approach

For each eligible source, the extraction matrix recorded the following: bibliographic metadata; evidence type, crop or environmental context, sensor and actuator hardware, communication technology, gateway–edge–cloud architecture, FMIS, ISOBUS/ISO 11783 or API connection, reported limitations, metrics, duration of deployment, calibration and maintenance information, metadata and data-quality mechanisms, security controls, and recommendations made by original authors.

Because the corpus intentionally combined empirical field evidence, previous reviews, standards, architecture papers, and conceptual proposals, a single quantitative risk-of-bias score was not applied. Instead, each source was weighted qualitatively according to its role in the synthesis. Direct field evidence was prioritized for reliability, and QoS claims, standards, and specifications were used for interoperability and security design requirements, and previous reviews were used primarily for contextual mapping and confirmation of recurring challenges.

Each source was coded against five synthesis categories—sensor robustness, calibration, and energy; connectivity and field QoS; Big Data management and FAIRness; interoperability with FMIS, machinery, and information models; and security, privacy, and governance—and against RQ1–RQ4 and G1–G10. This coding structure enables traceability from the reviewed evidence to Section 3 subsections, the gap matrix, and the design recommendations.

Table 1 summarizes the evidence type and traceability structure used in Section 3.

Table 1. Key evidence types, technological layers, associated research questions, and gap traceability used in the review synthesis.

Evidence Type	Primary Role in Synthesis	Representative References	Layer/RQ/Gap Traceability
Empirical field, equipment or communication studies	Highest weight for claims about hardware reliability, calibration, energy, packet delivery, latency, gateway location, and machinery integration.	[50–64]	Sensors and communication; RQ1, RQ3; G1–G5, G8
Previous reviews and broad surveys	Used to map recurring limitations, adoption barriers, and technology trends; not treated as direct evidence of field performance unless supported by primary studies.	[2–16,65–71]	Context and synthesis; RQ1–RQ4; all gaps
Normative standards and implementation specifications	Used to define interoperable data exchange, device management, messaging, observation semantics, and security baseline requirements.	[38–47,72,73]	Data/interoperability/security; RQ2–RQ4; G6–G9
Architecture, platform, and conceptual studies	Used to identify reusable software patterns, FMIS reference architectures, platform components, digital twins, and information-processing designs.	[18–21,74–76]	Architecture and FMIS; RQ2–RQ3; G6–G8
Security, privacy, ownership, and governance studies	Used to translate cybersecurity and data-ownership issues into practical threat models, access-control requirements, and data-sharing controls.	[11,45,46,69,77–86]	Security/governance; RQ4; G9–G10

3. Results

The results have been organized by infrastructure layers and linked explicitly to the research questions. Sections 3.1–3.3 focus primarily on RQ1, Section 3.4 addresses RQ2 and RQ3, Section 3.5 addresses RQ4, which relates to security and ownership rights, while Sections 3.6–3.8 summarize cross-layer design priorities and operational gaps.

3.1. IoT Architectures and Deployment Patterns in Precision Crop Production

In the literature, most networks continue to follow a multi-layer architecture in which the sensor layer (sensors and actuators) communicates with a gateway via an LPWAN, WSN, or mobile network connection and ultimately with cloud services for data storage and analysis [2,3,8]. This general architecture is now well established. The more uncertain question, however, is where each function should be located—at the node, the gateway, the edge server, or in the cloud—and how this distribution affects performance under field conditions.

Sapna et al. [10] demonstrate that today's edge computing literature has moved beyond simple cloud-based data processing and now examines hardware, sensors, communication capabilities, databases, and algorithm classes as an integrated design environment. Chamara et al. [63] further demonstrate that crop monitoring processes involving classification, segmentation, detection, and data collection can be shifted to the edge, which is directly relevant when bandwidth, latency, or connection continuity become limiting factors. The more general framework proposed by de Avila and Barbosa [9] is also useful because it reemphasizes that security, implementation costs, and the need for skilled professionals are not external constraints.

A common shortcoming is that studies on architecture continue to describe system layers primarily in qualitative terms, while providing too few comparative metrics. Transmission speed, end-to-end latency, local computational load, firmware-update capability, and diagnostic support are often mentioned but not regularly measured. As a result, many systems remain at the prototype demonstration stage rather than becoming a scalable reference architecture that could be implemented in practice.

The literature on this topic confirms that the placement of sensing, networking, and computing functions is still an open research question. Kalyani and Collier [67] reviewed hybrid cloud–fog–edge combinations applicable in smart agriculture, while Alharbi and Aldossary [87] proposed an energy-aware edge–fog–cloud partitioning strategy that clarifies the trade-off between communication and computing. Nawaz and Babar [88] extend this reasoning to environments with limited resources and point out that connectivity constraints, investment costs, and local service capacity should be addressed as primary planning parameters rather than secondary implementation issues.

TinyML-based agricultural edge network implementations [89] and IoT-compatible irrigation systems with embedded deep learning support [90] suggest that bringing computations closer to agricultural fields is feasible, but only if energy requirements, update mechanisms, and servicing limits are explicitly taken into account during design, rather than being ignored.

From a design perspective, the reviewed literature is synthesized in the reference architecture shown in Figure 2. The figure highlights that field deployment is not a simple linear sensor-to-cloud upload. Sensing and actuation, communication, edge/gateway processing, data and semantic services, FMIS, cloud decision support and machinery integration, cybersecurity, and serviceability must all be defined as interacting functions.

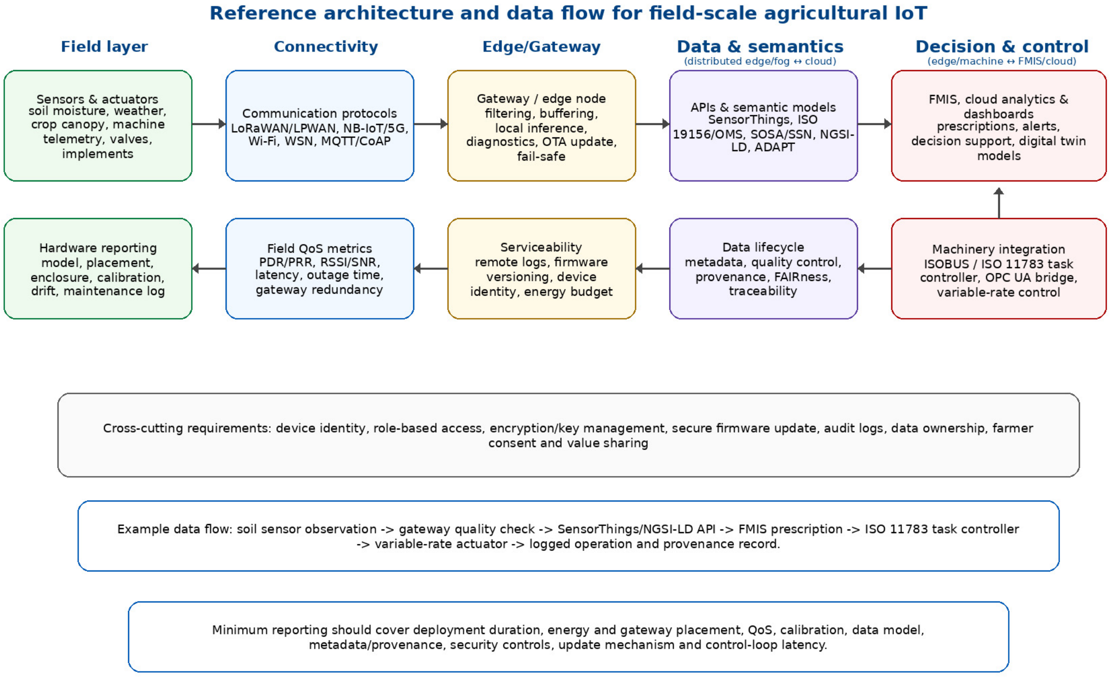

Figure 2. Distributed reference architecture and bidirectional data flow for agricultural IoT and Big Data infrastructures. Data and semantics span edge/fog and cloud services; decision and control span cloud/FMIS functions and latency-critical edge/machine control. Cross-cutting security, provenance, serviceability, and validation apply to every layer.

Figure 2 represents physical layers that are functional rather than fixed. The "Field" and "Connectivity" layers operate on sensors, actuators, machines, and communication infrastructure. Edge and gateway processing occurs locally, while the "Data" and "Semantics" layers are distributed between edge network services—for time-critical processing, buffering, timestamping, and quality control—and cloud services—for storage, integration, knowledge management, and deep analytics. Decision-making and control are also separated: dashboards, model programming, digital twins, and FMIS coordination are generally cloud-based, while the validation of operating instructions, fault-tolerant logic, manual overlay, and time-critical control are still performed at the edge or in the machine controller [30,33,36,67,87–90].

Input data includes sensor recordings, telemetry data, weather and imagery data, calibration and device status data, spatial coordinates, and FMIS data. Output data includes validated and visually annotated observations, events, record of source, and machine-readable information, which are provided via APIs or intermediary software. The OGC SensorThings API and the ISO 19156 standard (observations, measurements, and samples) define the structure of observations; SOSA and SSN support semantic interpretation; NGSI-LD represents contextual identities; MQTT supports messaging; LwM2M enables device management and ADAPT, or OPC UA links FMIS data to ISO 11783 and ISOBUS workflows [32–36,39–44,47,59–62,72,73,91,92].

Validation includes calibration, accuracy, timestamps, anomalies, message delivery, message authenticity, identifiers, units of measurement, coordinates, location, delay, fault tolerance, task file integration, and the feedback from the controller. In the example, a soil moisture observation is validated at the gateway, linked to an FMIS management zone and then adapted into an irrigation recommendation. After edge validation, the recommendation is transmitted via ADAPT or OPC UA to the ISO 11783 task controller, where it is processed and then returned as an applied record. In the event of a network failure, local buffering and the last validated safety rule ensure continuous operations until cloud-based synchronization restarts.

3.2. Sensor Networks: Hardware Reliability, Calibration, and Energy Constraints

The reviewed papers confirm that sensor nodes are still the most failure-prone part of the architecture. Both case studies and comprehensive reviews of sensors acknowledge sensor offsets, connector degradation, enclosure damage, and servicing burdens, but few specifically report on long-term multi-season behavior or failure rates [5,8]. This represents a serious limitation for crop production, where machinery traffic, tillage, spraying, and harvesting cause repetitive mechanical loads that are rarely taken into account in laboratory validations. In a three-season experiment carried out recently in a cereal field, calibrated NH_3 and environmental sensors were combined with 10 min LoRaWAN telemetry and a gateway–server–time series–dashboard workflow, which provided long-term evidence while also documenting cross-sensitivity among sensors, single-point sampling, and the requirements for locating reference measurement points in a single position [49].

The issue of calibration has been particularly underdeveloped. Mane et al. [50] demonstrated that the dielectric calibration of soil moisture continues to depend strongly on the soil and the field site, indicating that statements about "factory-calibrated" systems may be misleading when applied to other regions or seasons. More recent studies on sensor systems illustrate the same point from a different perspective. Nguyen et al. [53] combine heterogeneous sensing methods for soil moisture mapping, while Vahidi et al. [93] demonstrate multimodal fusion using drone-based ground-penetrating radar (GPR), RGB, and thermal imaging. Together, these studies suggest that a practical solution to the limitations of calibration and point measurement requires not only better sensors, but also better redundancy and better fusion strategies.

Autonomy remains a parallel limiting factor. Sadowski and Spachos [51] provide valuable experimental evidence that the communication layer strongly influences the operational lifetime of outdoor energy-harvesting systems; their comparison is particularly useful because it links technology selection to network longevity rather than just nominal range. Banđur et al. [52] similarly characterize energy efficiency as a system-level feature of WSN architecture rather than just a feature of the radio chip. From the perspective of field-deployable crop-production systems, the most critical unresolved need is a standardized method for reporting energy costs per unit of useful agronomic information, rather than reporting battery life as an isolated value.

These observations lead directly to three technical gaps: G1—insufficient multi-season reliability evidence; G2—limited embedded self-diagnostics and calibration intelligence; and G3—the lack of standardized energy-performance benchmarks for agricultural sensing systems.

Answer to RQ1 regarding the sensor layer: the main practical limitations were not only related to the accuracy of the sensors, but also to their physical stability over multiple seasons, site-specific calibration, replacement of connectors and housings, energy autonomy, and the lack of diagnostic reports. Future field studies should, therefore, report not only the official sensor specifications but also the number of malfunctions, service interventions, calibration deviations, and the amount of energy consumption per valid agronomic observation.

3.3. Communication Technologies and Field-Level Connectivity Limitations

The connectivity layer is one of the clearest areas where the recent literature adds genuinely new comparative evidence. Tao et al. [54] provide a synthesis of communication technologies for smart agriculture, but more recent papers reveal why generic technology summaries are not enough for system design. Wang et al. [55] show that the LoRaWAN adaptive data rate should be reconsidered for agricultural mobile sensor nodes rather than being treated as a static-network problem. Mahjoub et al. [56] demonstrate that path-loss behavior is strongly environment-specific, which challenges the widespread practice of quoting nominal LPWAN range values without local propagation modelling.

The limits of nominal specifications become even clearer for soil and subsurface applications. Moiroux-Arvis et al. [57] compare 433 MHz and 868 MHz LoRa performance for underground-to-aboveground communication, while Cotrim et al. [58] extend the discussion to a multi-hop underground network for soil-moisture monitoring. Together, these studies show that agricultural QoS cannot be reduced to line-of-sight range alone: frequency, burial depth, soil conditions, node mobility, and topology all matter. Therefore, single-gateway and single-scenario evaluations are not sufficient to justify technology deployment across different farm contexts. LoRa research focused on practical applications supports this conclusion. Singh et al. [94] demonstrated that low-cost, LoRa-based soil and weather monitoring is technically possible, but their practical usefulness depends not only on theoretical range claims but also on site-specific evaluation of network architecture, gateway configuration and connection stability.

The synthesis indicates that communication system planning in crop production must account for field-specific limitations, including crop canopy, soil conditions, moving agricultural machinery, fragmented land parcels, and temporary power supply. The literature still lacks a standardized evaluation framework that would allow farmers and engineers to compare the packet delivery ratio, latency, gateway redundancy, and network topologies across different experiments. These limitations correspond to G4—missing connectivity benchmarks—and G5—insufficient research on scalable, redundant topologies adapted to the geometry of real farms.

Recent studies on network architecture further support this view. Correia et al. [64] demonstrated that gateway location strategies can significantly influence uplink data rates and energy consumption, meaning that topology and efficiency must be considered together, rather than separating coverage data from quality-of-service outcomes. Together with the review by Villa-Henriksen et al. [15] on crop production, this suggests that studies on crop production communication should pay clearer attention to gateway positioning, the field geometry, and device mobility.

Answer to RQ1 for the communication layer: connectivity failure is strongly site- and topology-dependent. Comparable reporting should, therefore, include gateway coordinates and antenna height, crop and canopy conditions, device mobility, packet delivery ratio, RSSI/SNR distributions, latency percentiles, outage duration, and redundancy and failover behavior.

3.4. Big Data Management: Quality, Heterogeneity, and Interoperability Gaps

In this review, the concept of "Big Data" in field crop production is defined operationally rather than by dataset size alone. It refers to data infrastructures characterized by volume (e.g., GB ha−1 season−1), variety (sensors, machinery, weather, imagery, management guidelines, and farm records), velocity (sampling frequency, data frequency, and control-loop delay), and veracity (calibration, uncertainty, and handling of missing data and outliers), traceability (provenance, timestamps, spatial references, and operation logs), and lifecycle management (storage, retention, access, reuse, and deletion), which collectively determine the system's architecture and performance. This definition links Big Data directly to measurable infrastructure requirements rather than only to dataset size [22,23,27,65,66,68,95–98].

The challenges of data quality and reusability are equally significant. Top et al. [97] argue that the FAIR principles must be explicitly applied in agri-food systems; Chamorro-Padial et al. [66] reach a similar conclusion regarding openly available data, highlighting issues of licensing, metadata, and compatibility. The study by Krisnawijaya et al. [96] is particularly useful because it demonstrates that adhering to the FAIR principles in precision agriculture represents both a technological and an administrative challenge. Recent articles on multimodal sensing reinforce this interpretation: Nguyen et al. [53] and Vahidi et al. [93] show that, following the integration of heterogeneous sources, uncertainty management, metadata completeness, and repeatable preprocessing become far more important than simple file storage.

Interoperability remains the major integrative bottleneck. Urdu et al. [74] compare and align interoperability architectures for digital agri-food platforms, showing that architecture alignment is still an active problem rather than a settled standardization success. For machinery-linked crop systems, the literature on ISO 11783 and OPC UA is especially relevant. Oksanen et al. [61] established an early route for remote access to ISO 11783 process data via OPC UA, Backman et al. [60] showed how retrofit and ISOBUS-compatible equipment can be brought into a shared data-collection platform, Paraforos et al. [59] reviewed the industrial sensor/control landscape around ISO 11783, and Siponen et al. [62] proposed a next-generation task-controller concept based on OPC UA. Taken together, these papers show that syntax, semantics, and machinery integration all remain live research problems rather than back-office implementation details.

The literature on farm management information systems and interoperability architectures represents a complementary field that is still underrepresented in reviews of agricultural IoT. Studies on reference architectures and agricultural software ecosystems suggest that practical agricultural interoperability depends not only on data export but also on a modular software approach, common object descriptions, and configurable transformation paths between platforms [18–21,44].

These issues define G6—unclear operational meaning of Big Data in crop production, G7—missing agriculture-specific data-quality pipelines, and G8—insufficient validation of open machine-readable information models linking sensors, machinery, and agronomic entities.

Additional literature on data infrastructure points in the same direction. Saiz-Rubio and Rovira-Más [68] framed crop data management as a transition problem from smart farming toward Agriculture 5.0, emphasizing the need to manage data lifecycles, semantics, and decision support jointly. Amiri-Zarandi et al. [75] likewise argued for a platform-oriented view of smart farm information processing, shifting attention from isolated dashboards to reusable information-processing components. From a digital-twin perspective, Pylianidis et al. [76] further argued that agricultural twins only become operational when sensor streams, models, and management actions are connected through consistent information structures.

A related but often overlooked area is on-farm record-keeping and data collection. Basir et al. [99] demonstrated that the transition from analogue records to digital precision data collection remains uneven, which partly explains why metadata completeness, provenance and FMIS interoperability continue to be operational bottlenecks. Analyses of interconnected, data-driven precision agriculture likewise show that Big Data claims become meaningful only when they are linked to reusable analytical processes and compatible information structures [22,23,27,31–35,98].

At the information-model level, ISO 19156/observations, measurements, and samples, OGC SensorThings API and SOSA/SSN semantics provide a chain from observation concepts to API-level exchange and semantic interpretation, while ETSI NGSI-LD can support contextual publication and subscription across digital-twin and platform environments [32–36,39,40,43,72,73,91,92]. In a field data flow, a soil-moisture sensor observation can be timestamped and quality-flagged at the gateway, exposed through SensorThings or NGSI-LD, linked to a management zone in the FMIS, converted into a prescription or alert, transferred to ISOBUS/ISO 11783 task-controller workflows through an ADAPT/OPC UA-compatible interface, and finally logged as an as-applied operation with provenance and metadata.

Table 2 is presented in Section 3 as a traceability table; it shows how the study used the selected recent studies and standards to support specific parts of its analysis, rather than presenting them as indiscriminate background references.

Table 2. Representative recent studies and specifications incorporated into the review and their comparative contribution to the design-oriented synthesis.

How the Result Is Used in This Review	New Result or Comparison Contributed by the Study	Study
Used to strengthen the architecture section and justify edge-versus-cloud as a design problem, not just an implementation choice.	Systematic edge-computing architecture for smart agriculture; highlights bandwidth, latency and unexplored methods such as transformers.	Sapna et al. [10]
Used as empirical support that local intelligence can reduce data transfer and improve responsiveness.	Edge deployment of classification, segmentation, detection, and counting models for crop monitoring.	Chamara et al. [63]
Used to sharpen the calibration/drift argument and explain why nominal sensor accuracy is insufficient.	Dedicated review of soil-moisture sensor calibration methods and site-specific constraints.	Mane et al. [50]
Used to argue that LPWAN benchmarking must consider movement and changing link conditions.	Adaptive data rate redesigned for agricultural mobile nodes.	Wang et al. [55]
Used to challenge generic range claims and motivate local propagation evidence.	Environment-specific LoRa path-loss modelling in a crop-relevant outdoor setting.	Mahjoub et al. [56]
Used to extend the communication discussion beyond aboveground static networks.	Underground and multi-hop LoRa studies show frequency- and topology-sensitive behavior for soil monitoring.	Moiroux-Arvis et al. [57]; Cotrim et al. [58]
Used to make "big data" claims operational and infrastructure-oriented.	Digitization footprint in GB ha^{-1} links sensing intensity to storage and transfer requirements.	Kayad et al. [95]
Used to move data quality from a generic challenge to a design and governance problem.	FAIR implementation requires both technical pipelines and organizational alignment.	Krisnawijaya et al. [96]; Top et al. [97]
Used to frame machinery and farm management information systems integration as a standards-validation problem.	Interoperability architecture alignment and OPC UA-based task-controller evolution.	Urdu et al. [74]; Siponen et al. [62]
Used to translate security/privacy from abstract concern to concrete architectural patterns.	Privacy-preserving FL and secure OPC UA routes reduce raw-data exposure and insecure CAN exchange.	Durrant et al. [78]; Dembani et al. [79]; Brodie and Oksanen [80]

3.5. Security, Privacy, and Data Ownership in IoT-Based Crop Production

Security remains one of the least mature dimensions of the literature relative to its importance for field deployment. A farm IoT threat model should start with critical assets—sensor readings, actuator commands, machine task files, credentials, firmware images, FMIS records, location data, and farmer-owned datasets—and then identify actors, attack surfaces and device, network, gateway, cloud, and machinery layers [11,45,46,69,83,84].

The latest literature on data security also brings a new perspective to the discourse. Durrant et al. [78] demonstrate why collaborative learning across sectors is valuable in the agri-food industry, where stakeholders may be reluctant to share raw data, while Dembani et al. [79] expand this discussion with a more comprehensive overview of data protection techniques and their potential applications in agriculture. In the case of machine-related crop production systems, the study by Brodie and Oksanen [80] is particularly relevant, as it directly links cybersecurity with ISO 11783/CAN communication security via OPC UA. Together, these studies transform data protection and security from theoretical concerns into concrete architectural patterns.

Data ownership and value generation are not just legal or social issues. Uyar et al. [81] demonstrate that valuable insights derived from agricultural data depend on how the data are shared, synthesized, and transformed into services. Similarly, Wolfert and Isakhanyan [82] argue from the perspective of farmers that monitoring progress in digital sustainability requires specific sociotechnical frameworks.

The implication is that access control, auditability, privacy-preserving learning, and value-sharing logics should be treated as architectural requirements rather than ex post governance add-ons. These themes define G9—missing lightweight, farm-suitable end-to-end security and ownership patterns.

Other sources in the security literature indicate that this is not just an application-layer issue. Gupta et al. [83] reviewed the data protection and security challenges of smart agriculture at the device, network, and cloud layers, while Nikander et al. [84] translated this discussion more directly into requirements for agricultural communication networks. Yazdinejad et al. [69] subsequently systematized the vulnerabilities, challenges, and defenses in the field of smart farming and precision agriculture, while Khullar [85] presented a specific privacy-preserving architecture that combines machine learning with blockchain-based, secure IoT classification. Based on these studies, Rouzky et al. [86] point out that administrative shortcomings in the areas of data protection, security, and data sharing still exist, even when the necessary digital infrastructure already exists.

Furthermore, the latest research on data management in the agri-food sector suggests that regulatory frameworks must be translated into concrete operational requirements, including identification of tools, role-based access control, auditable data sharing, and transparent value addition for farmers and other stakeholders. In this context, secure data sharing is not an external add-on but an integral part of the interoperability infrastructure, particularly when reusability and long-term usability are explicit engineering goals [77].

Table 3 presents the security analysis in the form of a specifically farm-oriented threat model. The control measures are intentionally simple, as many field nodes have limited resources and must continue to be managed by farm staff or local service providers.

Table 3. Farm-oriented IoT risk model for precision crop-production infrastructures.

Asset–Actor	Typical Attack Surface	Risk for Crop-Production System	Lightweight Feasible Controls
Sensor nodes and firmware, attacker: opportunistic local or remote actor	Unprotected debug ports, weak credentials, insecure firmware update, physical access in field	False observations, node takeover, battery drain, unavailable data stream	Unique device identity, signed firmware, disable default credentials, tamper-evident enclosure, update log
Gateways and edge devices, attacker: remote intruder or malicious insider	MQTT/HTTP/CoAP endpoints, Wi-Fi/cellular router, local storage, admin interface	Data manipulation, service outage, pivot into FMIS/cloud	TLS/DTLS where feasible, role-based accounts, firewall rules, local buffering, audit logs, backup configuration
Machine/ISOBUS/CAN and task-controller data, attacker: compromised device or service laptop	CAN bus, ISO 11783 messages, USB/import files, service tools	Incorrect variable-rate actuation, unsafe control command, corrupted task files	OPC UA bridge with security, signed task files, manual override, validation of prescription bounds
Cloud/FMIS/API data, actor: vendor, platform operator, external attacker	APIs, user roles, data-sharing contracts, third-party analytics	Loss of ownership, unauthorized sharing, privacy, and business-risk exposure	Role-based access, consent and purpose limitation, provenance, export logs, privacy-preserving analytics

3.6. Socio-Technical Constraints and Implications for Technical Design

Although this review focuses on technological boundaries, the literature reviewed shows repeatedly that costs, expertise, service availability, and trust determine which technological architectures can be implemented in practice. Rajak et al. [5], Shahab et al. [8], and de Avila and Barbosa [9] all highlight implementation costs and expertise as persistent obstacles. From a system architecture perspective, it is important that these challenges translate into measurable technological constraints: low total cost of ownership, minimal field service, simpler deployment, transparent user interfaces and upgrade paths that do not require highly specialized on-site support.

Socio-technical constraints must be translated into technical design aims rather than treated as external adoption barriers. For G10, measurable indicators include total cost of ownership per hectare and season, installation time per field, number of service visits, training hours required for routine operation, time to diagnose a failed node, spare-part availability, number of manual metadata-entry steps, and user success rate for common tasks. These indicators allow cost, skills, support, and trust to become testable design requirements.

3.7. Cross-Layer Synthesis: Four Key Design Tensions

When findings are interpreted across layers rather than within isolated component categories, four recurring design tensions emerge. First, reliability versus cost: robust housings, redundant gateways, and richer diagnostics improve dependability but increase hardware and service costs. Second, connectivity versus energy: higher sampling and transmission rates improve timeliness but shorten lifetime and increase maintenance burden. Third, data richness versus manageability: additional sensing modalities can improve inference quality while increasing metadata, storage, and synchronization demands. Fourth, security versus usability: stronger protection can complicate commissioning, updates, and daily operation unless adapted to farm realities. Figure 3 and Table 4 summarize these tensions and the associated gap logic.

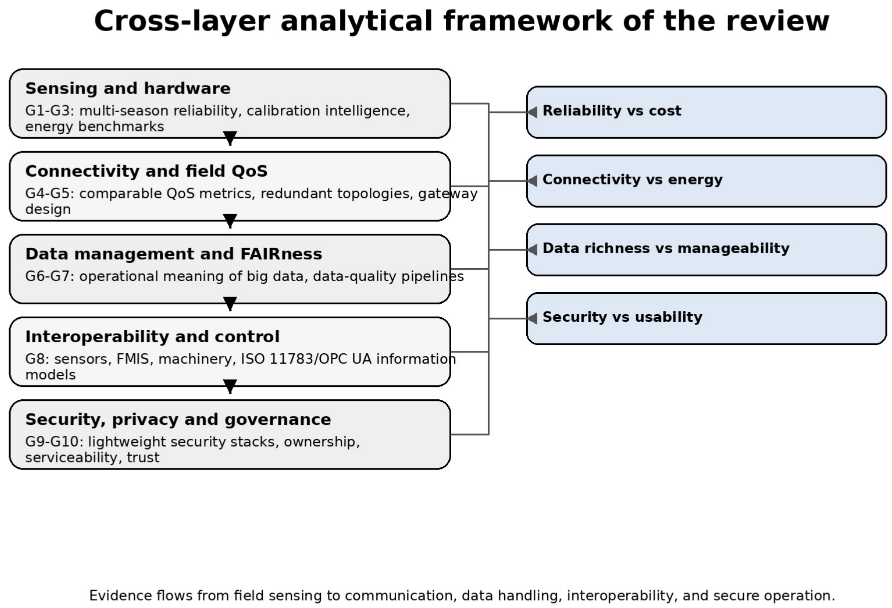

Figure 3. Cross-layer analytical framework of the review, linking infrastructure layers, gap clusters (G1–G10), and recurring design tensions.

Table 4. Operationalized G1–G10 gap matrix with indicators, metrics, evaluation designs, and priority levels.

Gap	Measurable Indicators—Example Metrics	Recommended Evaluation Design	Priority
G1 multi-season reliability	Failure rate per season; MTBF; uptime; maintenance interventions ha^{-1} season^{-1}; enclosure/connector failures	Multi-season field logs covering tillage, spraying, irrigation, and harvest operations	High
G2 diagnostics and calibration	Calibration drift; RMSE against reference; anomaly-detection precision/recall; auto-calibration success rate	Reference-sensor comparison plus drift tracking across soils, seasons, and maintenance events	High
G3 energy performance	Energy per valid observation; mAh day^{-1}; duty cycle; recharge balance; battery replacement interval	Energy budget under realistic sampling, transmission, and sleep schedules	High
G4 field connectivity QoS	Packet delivery ratio; RSSI/SNR; p95 latency; outage duration; path-loss parameters	Replicated field trials with crop canopy, soil, mobility, and gateway-location metadata	High
G5 scalable redundant topology	Gateway redundancy; coverage probability; failover time; mobile-node handover success	Compare single, redundant, and hybrid fixed/mobile topologies on fragmented fields	Medium–High
G6 operational Big Data definition	GB ha^{-1} season^{-1}; data modalities; sampling frequency; retention period; edge/cloud split	Report complete data lifecycle from sensing to storage, reuse, and deletion	Medium–High

Table 4. *Cont.*

Gap	Measurable Indicators—Example Metrics	Recommended Evaluation Design	Priority
G7 FAIR/data-quality pipelines	Metadata completeness; missing values; quality flags; provenance capture; preprocessing reproducibility; FAIR score	Publish data-quality pipeline, uncertainty rules, and machine-readable metadata with datasets	High
G8 semantic and machinery interoperability	FMIS/ISO 11783/OPC UA/API mapping success; semantic round-trip loss; conformance tests	End-to-end interoperability test from sensor observation to machine task and logged operation	High
G9 lightweight security and ownership	Device identity coverage; secure-update success; credential rotation; access-control coverage; encryption overhead; auditability	Threat-model-based security benchmark for constrained farm devices and platforms	High
G10 serviceability, cost and skills	TCO ha^{-1} $season^{-1}$; installation hours; training hours; maintenance tickets; diagnostic time; user task success rate	Co-design evaluation with farmers, technicians, and vendors over an operating season	Medium–High

3.8. Direct Answers to the Research Questions

RQ1—A1. *Field limits primarily refer to the resilience of sensor nodes, calibration deviations, energy independence, and the quality of service (QoS) of the network. Available data indicate that standard specifications are insufficient without studies that include logs spanning multiple growing seasons and reports of maintenance frequency, message delivery rates, and latency under field conditions specific to the crop in focus.*

RQ2—A2. *Edge-to-cloud architectures improve response time only if caching, local processing, metadata logging, secure updates, and traceability are addressed. Usability and scalability depend on where filtering, quality control, and decision logic are located on the node–gateway–cloud spectrum.*

RQ3—A3. *Challenges related to integration occur at the semantic, syntactic, and operational levels: sensor observations must be linked to agronomic objects, FMIS records, ISO 11783 task-driven workflows, OPC UA/CAN paths, and reusable APIs. Ad hoc exports do not provide sufficient interoperability for closed control loops.*

RQ4—A4. *Among the most important future challenges are multi-season, benchmark-supported availability, comparable field quality of service (QoS), data quality processes that meet FAIR requirements, validated open information models, lightweight end-to-end security and serviceability, and cost metrics that demonstrate maintainability at farm scale.*

4. Discussion

4.1. Contribution Relative to Earlier Surveys

In contrast to broad digital-agriculture surveys, this review organizes findings by deployment failure modes and design requirements. This focus makes the contribution of the manuscript explicit. It shows where open-field crop-production systems fail across the sensing, communication, data, interoperability, security, and serviceability layers, and it translates those limitations into indicators and reporting requirements.

The process-oriented approach also illustrates why many of the general conclusions found in the literature must be interpreted with restraint. Review articles and theoretical studies are valuable for mapping technological trends, but empirical field studies provide more concrete evidence to support arguments about stability, delays, power consumption, and calibration. Standards and reference architectures provide effective guidance on interoperability, but they still need to be validated within the context of machine-related agricultural processes.

The overview, therefore, separates the types and weights of the evidence before drawing conclusions. The G1–G10 matrix should be interpreted as a research and reporting framework, not as evidence that all gaps have the same level of empirical support. G1, G4, and G8 are supported by direct field or machine evidence; G6, G7, and G9 are based primarily on standards, platform studies, and the architecture and security literature, and G10 requires a combined technical and socio-economic assessment.

This systems perspective matches previous research demonstrating that innovations in Agriculture 4.0 depend more on the integration of sensing, analysis, data infrastructure, and decision support than on a separate addition of digital infrastructure [14,16,76].

4.2. Benefits for System Evaluation and Architecture

Future studies should report more than conceptual novelty or proof-of-concept performance. For field-installable systems, the minimum reporting package should include deployment duration, crop and field context, sensor placement, calibration method, maintenance events, energy budget, gateway location, antenna configuration, packet delivery, latency, models, metadata, update procedure, security controls, and the route from sensing to control. Table 5 translates these requirements into a practical checklist.

Table 5. Minimum reporting requirements for agricultural IoT and Big Data infrastructure studies.

Reporting Domain	**Minimum Items to Report**
Deployment context	Crop, field size, soil and topography, season, duration, weather exposure, relevant field operations, and machinery traffic.
Hardware and calibration	Sensor/actuator model, enclosure, placement depth/height, calibration procedure, reference measurements, drift checks, and maintenance/failure log.
Energy and serviceability	Battery/harvesting capacity, duty cycle, energy budget, firmware version, update method, diagnostic logs, service visits, and replacement intervals.
Connectivity and gateway design	Protocol, frequency/band, antenna and gateway coordinates/height, topology, packet delivery ratio, RSSI/SNR, latency percentiles, and outage/failover data.
Data management and interoperability	Timestamp/spatial reference, units, metadata schema, quality flags, preprocessing, provenance, storage/retention, API, FMIS link, and ISO 11783/ISOBUS/OPC UA/ADAPT mapping where relevant.
Security, privacy, and ownership	Device identity, authentication/authorization, encryption or compensating controls, credential handling, secure update, audit logs, data-access roles, and consent and ownership/value-sharing arrangements.
Decision/control loop	Decision rule or model, control latency, fail-safe state, manual override, prescription validation, actuator feedback, and logged operation record.

A second implication is that open-field crop-production systems should be planned as interconnected technical-service systems rather than isolated sensing experiments. The strongest architecture studies integrate sensing, communications, data quality, standards, machine interfaces, and management processes into designs that remain interpretable beyond pilot demonstrations.

Long-term operability should, therefore, be treated as a primary design criterion. Publish/subscribe messaging, standardized management, secure firmware-update services, and context-based APIs improve interoperability only when they are integrated at the beginning of system design and reported with enough detail to be replicated [41–43,45,46,100].

4.3. Priority Research Directions

Four priority research directions emerge. First, benchmark suites are needed for multi-season reliability, calibration drift, energy cost, and field-level QoS so that claims become comparable across crops, sites, and operating seasons. Second, reference architectures should connect sensors, gateways, edge/cloud services, FMIS interfaces, and ISO 11783/ISOBUS machinery through explicit information models rather than ad hoc connectors. The allocation of individual functions to nodes, gateways, edge networks, the cloud, FMIS, or machine control systems must be reported along with inputs, outputs, standards, validation criteria, and backup behavior. A recent review ranging from policy to engineering practice similarly links measurable sustainability indicators to sensing, analysis, and operational capabilities and identifies safety regulations as scaling limitations for controllable smart agricultural systems [48].

Third, data infrastructures should be FAIR-aware and uncertainty-aware by default, exposing metadata completeness, preprocessing, alignment, provenance, and cleaning steps as reportable outputs. Fourth, cybersecurity and privacy should move from end-stage add-ons to lightweight, farm-suitable design patterns, including device identity, role-based access control, secure update pathways, auditability, and privacy-preserving analytics.

These priorities will become more urgent as 5G, AIoT, digital twins and more capable AI models increase sensing density, model complexity, and bidirectional data flow across agricultural infrastructures [70,71,101,102]. Without stronger reporting and benchmarked architectures, increased model complexity may amplify rather than solve integration, security, and maintainability problems.

4.4. Limitations of This Review

This review has limitations that should be stated explicitly. The corpus combines heterogeneous evidence types, including empirical field studies, reviews, standards, architecture proposals, and conceptual papers; therefore, not all conclusions have the same evidential weight. The search focused on 2020–2025 literature with selected 2026 updates and older foundational studies or standards where necessary. Because outcome measures were heterogeneous, a quantitative meta-analysis was not feasible, and architectures could not be ranked directly. Database coverage, Google Scholar ranking effects, and the inclusion of normative documents outside bibliographic databases may limit reproducibility despite the reported PRISMA-type counts and coding rules. The proposed architecture and G1–G10 matrix should, therefore, be treated as design and reporting frameworks requiring validation in multi-season field deployments.

5. Conclusions

IoT and Big Data infrastructures in precision crop production are limited less by the absence of individual components than by the difficulty of integrating those components into reliable, calibrated, interoperable, secure, and serviceable field systems. Regarding the "Data and Semantics" and "Decision-Making and Control" layered structures, latency-sensitive quality control, fault-tolerant logic, and the validation of control procedures must continue to be field-based, while the long-term archiving of data, integration between systems, dashboards, model programming, and digital twin services can be cloud-based. The revised synthesis shows that the most persistent barriers concern multi-season hardware evidence, field-specific connectivity benchmarking, operational Big Data definitions, FAIR-aware metadata and data-quality pipelines, machinery/FMIS interoperability, and lightweight security and ownership patterns. By distinguishing evidence types, answering the research questions explicitly, proposing a distributed reference architecture with explicit inputs, outputs, standards, and validation points, operationalizing the G1–G10 matrix, and defining minimum reporting requirements, this review turns general limitations into measurable design and evaluation targets. The conclusions should, therefore, be interpreted as a research agenda grounded in a heterogeneous corpus rather than as a quantitative performance estimate or technology ranking. In practical terms, the route from sensing through control and feedback must become explicit, measurable, and serviceable if digital crop-production systems are to scale beyond pilot deployments.

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