

ORIGINAL RESEARCH

Open access

An Interoperable Reference Architecture for Smart Farming Platforms: Integrating Sensors, Machinery, Farm-Management Systems, APIs, and Analytics

David Osei^{1*}, Akua Afriyie¹, Kofi Adu²

Abstract

Smart farming platforms are becoming central infrastructures for digital agriculture because they connect field-level sensing, machinery records, farm-management information systems, remote sensing inputs, advisory services, analytics modules, and decision-support tools. Yet many platforms remain limited by fragmented data flows, incompatible formats, weak semantic alignment, uneven governance arrangements, and poor integration with farm decision workflows. This article develops an interoperable reference architecture for smart farming platforms. The approach is conceptual and architecture-oriented: it synthesises platform, IoT, farm-management, interoperability, analytics, and governance concerns into a layered architecture that clarifies how heterogeneous agricultural data and services can be connected, interpreted, governed, analysed, and reused. The proposed architecture includes physical sensing and machinery, connectivity and edge computing, data ingestion, APIs and integration, data standardisation and semantic interoperability, storage and governance, analytics and AI, decision-support and visualisation, farm-management workflow, stakeholder interface, security and access control, and monitoring and feedback layers. The contribution is a structured architecture that distinguishes data connectivity, API access, syntactic compatibility, semantic interoperability, governance, analytics integration, and workflow usability. The article argues that interoperable smart farming platforms should not be treated as simple data repositories or dashboards; rather, they require modular, auditable, secure, and context-sensitive integration across technical and organisational boundaries. The architecture supports researchers, platform developers, machinery manufacturers, FMIS providers, advisors, cooperatives, and policymakers in designing more coherent digital agriculture ecosystems.

Keywords Precision agriculture, Interoperability, Digital agriculture, Farm management information systems, APIs, Agricultural analytics

*Correspondence:

David Osei

david.osei@ug.edu.gh

¹ Department of Agricultural Platform Architecture and Integration, Faculty of Agriculture, University of Ghana, Accra, Ghana

² Department of Interoperability and Farm Management Systems, Faculty of Agriculture, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana

Introduction

Smart farming platforms have become core infrastructures in digital agriculture because they are expected to organise heterogeneous data, coordinate multiple technologies, and support more informed farm-management decisions. The reviewed smart farming literature shows that digital agriculture depends on data streams generated by sensors, machinery, remote sensing systems, farm records, advisory systems, and analytics tools, but these streams do not automatically become usable knowledge when they are merely collected in a shared environment [1–3]. For this reason,

smart farming platforms should be understood as data ecosystems in which technical connectivity, data management, institutional arrangements, and user practices interact.

The integration challenge is not only technological. IoT-based food and farm systems have been examined through architecture frameworks precisely because device connectivity, data exchange, service coordination, and decision support require structured system design rather than ad hoc platform assembly [4]. In smart farming, a platform that receives data from a soil probe, a tractor terminal, a weather service, a satellite image, and an FMIS must make these data technically accessible, syntactically manageable, semantically interpretable, governable, and usable within farm operations.

Interoperability therefore matters because smart farming increasingly depends on cross-system data reuse. A yield monitor may produce spatially referenced observations, a sprayer may generate variable-rate application records, a weather station may provide high-frequency time series, and an FMIS may store field boundaries, crop plans, input records, and advisory notes. Without an architecture that clarifies how these elements are connected, standardised, governed, and translated into decisions, platform integration can remain limited to data aggregation rather than meaningful operational interoperability [1].

This article develops an interoperable reference architecture for smart farming platforms. The aim is not to present a software implementation, empirical benchmark, vendor comparison, or universal platform prescription; instead, it proposes a conceptual architecture that clarifies platform layers, data flows, interoperability mechanisms, governance responsibilities, analytics integration, and decision-support functions. Such a reference architecture is useful because it provides a reusable design logic that can be adapted to diverse farm contexts, technology portfolios, institutional arrangements, and data-governance requirements [4].

Smart Farming Platforms as Integration Systems

Smart farming platforms can be defined as integration systems that connect field-level data sources, machinery systems, farm-management records, remote sensing inputs, advisory knowledge, analytics modules, and decision-support interfaces. Their function is broader than storing data in a central repository because they must coordinate interactions among devices, software services, users, data standards, governance rules, and decision contexts. Recent smart farming scholarship shows that smart farming systems combine sensing, connectivity, automation, information processing, and decision support across diverse agricultural operations [5].

Data aggregation, interoperability, analytics integration, and workflow integration are related but distinct platform functions. Data aggregation refers to collecting information from different sources; interoperability concerns whether systems can exchange, interpret, and reuse data across technical and organisational boundaries; analytics integration concerns whether data can support descriptive, predictive, or prescriptive reasoning; and workflow integration concerns whether outputs are embedded in farm planning, field operations, advisory routines, and recordkeeping. Crop data management is therefore a platform-level function because data must be prepared, contextualised, and maintained across the farm-data lifecycle before it can support operational decisions [6].

The value of a smart farming platform depends on modularity because agricultural technologies evolve at different speeds and are adopted in diverse combinations. Sensors, machinery terminals, FMIS tools, drone imagery, satellite products, advisory portals, and analytics modules may enter the platform ecosystem through different vendors, data formats, update cycles, and ownership arrangements. Agriculture 4.0 scholarship emphasises that smart farming depends on multiple enabling technologies, which means that platform design should support modular integration rather than assume one closed system can provide all capabilities [7].

However, modularity alone is insufficient. Platform usefulness also depends on data quality, governance, usability, and decision relevance. Poorly documented sensor readings, inconsistent field identifiers, missing timestamps, unclear data

rights, inaccessible APIs, or dashboards disconnected from farm routines can all reduce the value of technically integrated systems. A smart farming platform should therefore be designed as an adaptive integration environment that supports data movement, shared meaning, trustworthy governance, analytical reuse, and practical decision-making [6].

Sensors, Machinery, and Farm-Management Systems

The physical sensing and machinery layer of a smart farming platform includes IoT sensors, soil sensors, weather stations, livestock and crop-monitoring devices, machinery telemetry, yield monitors, and variable-rate application systems. These systems generate data with different temporal frequencies, spatial granularities, calibration needs, and operational meanings. Agricultural IoT research shows that connected sensing can support monitoring and automation, but it also introduces challenges related to device heterogeneity, deployment conditions, communication reliability, and data integration [8].

Sensor and device data usually require preprocessing before they can be used in analytics or decision support. Raw observations may need timestamp alignment, spatial referencing, unit conversion, anomaly detection, missing-value handling, and contextual linkage to fields, crops, operations, or management zones. IoT and data analytics research in agriculture highlights that value emerges when data collection is connected to analysis and interpretation rather than treated as a separate technical endpoint [9]. This makes the data ingestion layer essential for transforming physical signals into platform-ready information.

Machinery telemetry, yield monitor data, and variable-rate application records add further integration complexity because they are often linked to equipment-specific systems, field operations, geospatial paths, and proprietary data structures. Smart farming IoT solutions demonstrate that device ecosystems differ in sensing functions, connectivity arrangements, data models, and deployment architectures, so platforms must be prepared for heterogeneous machine-generated data rather than assuming uniform data streams [10]. Integration must therefore address not only data availability but also operational context, spatial reference systems, equipment metadata, and task-specific meaning.

Farm-management information systems and advisory records form another critical input category because they connect platform data to planning, compliance, agronomic interpretation, and management routines. FMIS research shows that these systems include diverse functions such as recordkeeping, planning, monitoring, reporting, and decision support, but they also face obstacles related to usability, data entry burden, integration, and alignment with farm workflows [11]. As a result, smart farming platforms should treat FMIS integration as a workflow and organisational challenge, not merely as a database-connection task.

Table 1 summarises the major smart farming platform input systems that require integration across sensors, machinery, remote sensing, and farm-management systems.

Table 1. Smart Farming Platform Input Systems Requiring Integration: IoT Sensors, Machinery Telemetry, Yield Monitors, Variable-Rate Application Records, Remote Sensing, Weather Data, Soil Data, Farm-Management Information Systems, and Advisory Records

Input system	Typical data generated	Data format or structure	Temporal frequency	Spatial granularity	Integration challenge	Data-quality concern	
IoT field sensors	Soil moisture, temperature, humidity, crop microclimate, water status	Time-series observations, device logs, sensor metadata	High-frequency to periodic	Point, zone, or field level	Device heterogeneity, communication gaps,	Missing values, drift, sensor failure, inconsistent units	cc

					calibration differences		
Weather stations	Rainfall, wind, temperature, humidity, solar radiation	Time-series data with station metadata	High-frequency to daily summaries	Station, farm, or local area	Linking station data to fields and operations	Sensor exposure, missing periods, local representativeness	e c
Soil data systems	Soil texture, nutrients, pH, organic matter, compaction, electrical conductivity	Laboratory records, spatial layers, sampling grids, maps	Seasonal, annual, or periodic	Point, grid, zone, or field level	Aligning sampling schemes with field boundaries and management zones	Sampling bias, inconsistent laboratory methods, outdated layers	Pr
Farm machinery telemetry	Machine location, operation status, fuel use, implement activity, task logs	Geospatial logs, machine messages, equipment metadata	Real time, per operation, or batch upload	Path, field, machine, or operation level	Proprietary formats, equipment-specific identifiers, connectivity variation	Incomplete task records, inconsistent implement metadata	C c
Yield monitors	Yield, moisture, harvest location, crop flow observations	Georeferenced point or raster-like harvest records	Per harvest operation	Path, grid, zone, or field level	Cleaning, calibration, spatial alignment, boundary matching	Outliers, lag effects, sensor calibration errors	ou
Variable-rate application systems	Prescription maps, applied rates, input type, application location	Geospatial prescriptions and as-applied records	Per application operation	Grid, zone, path, or field level	Reconciling planned and actual application records	Missing as-applied data, unit inconsistency, boundary mismatch	rec
Remote sensing systems	Vegetation indices, canopy condition, thermal indicators, imagery-derived layers	Raster imagery, processed layers, metadata	Event-based, periodic, or seasonal	Pixel, zone, field, or landscape level	Cloud cover, resolution differences, georeferencing, temporal matching	Atmospheric effects, classification error, inconsistent preprocessing	b
Farm-management information systems	Field records, crop plans, input records, labour tasks, compliance documents	Relational records, forms, calendars, field-boundary files	Continuous, seasonal, or event-based	Farm, field, crop, enterprise, or task level	Workflow alignment, duplicate entry, inconsistent identifiers	Incomplete records, manual-entry errors, outdated plans	o a

Advisory records	Recommendations, scouting notes, risk assessments, agronomic observations	Text notes, reports, structured forms, attachments	Event-based or seasonal	Field, crop, farm, or advisory territory	Combining expert interpretation with platform data models	Ambiguity, inconsistent terminology, limited metadata	
------------------	---	--	-------------------------	--	---	---	--

APIs, Data Standards, and Interoperability Layers

APIs provide controlled mechanisms through which software systems can request, exchange, update, and reuse agricultural data. In a smart farming platform, an API layer can connect sensor services, machinery data portals, FMIS tools, analytics modules, advisory applications, and dashboards, but API access should not be mistaken for full interoperability. The AgDataBox API demonstrates the importance of integration mechanisms for precision agriculture data and software, while data-standard and semantic-model research shows that exchange mechanisms require format alignment, metadata, and shared interpretation to become reusable across systems [12–14].

Data standards and metadata support syntactic and contextual consistency. Syntactic interoperability concerns whether data can be exchanged in recognised formats and structures, whereas metadata helps describe units, timestamps, spatial references, sensor properties, field identifiers, crop context, operational events, and data provenance. Data standards can reduce fragmentation by making information more consistent, but they do not remove the need for governance, semantic interpretation, data-quality management, or workflow alignment [13]. Therefore, the architecture should position standards as part of a wider interoperability stack rather than as a standalone solution.

Semantic interoperability is especially important because agricultural data often carry meaning that depends on context. A “field,” “zone,” “operation,” “application,” “yield,” or “recommendation” may be represented differently across machinery systems, FMIS tools, advisory services, and analytics modules. Semantic meta-models for precision agriculture and livestock farming show that integrated data exploitation requires shared concepts and relationships, not only shared files or database fields [14]. Ontologies, controlled vocabularies, metadata models, and semantic mappings can therefore help platforms preserve meaning across heterogeneous systems.

Interoperability should be designed as layered architecture rather than simple file transfer. Recent interoperability architecture work for digital agri-food platforms shows that technical, semantic, organisational, and governance dimensions must be aligned for data and services to move across platform boundaries in reusable ways [15]. This distinction is critical: data connectivity enables access, API integration enables controlled exchange, format compatibility enables parsing, semantic interoperability enables shared meaning, governance enables legitimate use, and workflow integration enables practical decision-making.

Table 2 maps the interoperability layers required for smart farming platforms to exchange, interpret, and reuse heterogeneous agricultural data.

Table 2. Interoperability Layers for Smart Farming Platforms: Technical Connectivity, Data Formats, APIs, Metadata, Semantic Alignment, Data Standards, Governance Rules, Security, Privacy, and Cross-Platform Portability

Interoperability layer	Core function	Technical mechanism	Required metadata or standardization	Main barrier	Governance consideration	Platform design implication

Technical connectivity	Enables devices, systems, and services to transmit data	Networks, gateways, edge devices, device connectors, communication protocols	Device identity, connection status, timestamp, location, data-source description	Unreliable connectivity, incompatible devices, limited rural infrastructure	Responsibility for connectivity failures and data continuity	Design redundant and context-aware connectivity pathways
Data-format compatibility	Allows systems to parse and structure exchanged data	Common file formats, schemas, database mappings, geospatial formats	Units, field identifiers, coordinate systems, schema definitions	Proprietary formats, inconsistent field names, undocumented structures	Rules for format conversion and data transformation accountability	Include transformation services and schema-validation checks
API integration	Provides controlled software-to-software exchange	REST APIs, service interfaces, authentication, event-based data exchange	Endpoint documentation, permissions, object definitions, version information	Closed APIs, version changes, weak documentation, uneven access	API access rights, consent, rate rules, audit trails	Use modular API gateways and version-managed interfaces
Metadata management	Describes context, provenance, quality, and meaning	Metadata registries, data catalogues, provenance records	Source, owner, collection method, time, location, processing history, quality flags	Missing metadata, inconsistent terminology, manual-entry burden	Data provenance, accountability, permitted reuse	Make metadata capture part of ingestion and workflow design
Semantic alignment	Preserves shared meaning across systems	Ontologies, semantic mappings, controlled vocabularies, domain models	Concept definitions, relationship mappings, crop and operation terminology	Different meanings for similar terms across platforms	Agreement on authoritative terms and interpretation rules	Include semantic services between data standards and analytics
Data standards alignment	Reduces fragmentation across data exchange practices	Standard schemas, domain data models, exchange templates	Standard units, spatial references, crop codes, operation categories	Partial adoption, local adaptation, vendor divergence	Standard-selection authority and update responsibilities	Design standards support without locking the architecture to one format
Governance rules	Defines legitimate data access, control,	Permission models, consent records, data-	Ownership, access rights, purpose of use, retention rules	Unclear data rights, weak transparency,	Farmer control, benefit sharing,	Embed governance services across

	sharing, and reuse	use policies, audit logs		misaligned incentives	institutional accountability	ingestion, APIs, storage, and analytics
Security and privacy	Protects systems, data, and users from misuse or attack	Authentication, authorisation, encryption, monitoring, secure logging	User identity, role definitions, sensitivity tags, access history	Cybersecurity threats, weak credentials, poorly secured devices	Privacy protection, incident accountability, access-control enforcement	Treat security as cross-cutting rather than an add-on
Cross-platform portability	Allows data and services to move across platform ecosystems	Export/import services, open interfaces, semantic mappings, data packages	Portable identifiers, standard metadata, provenance, licensing terms	Vendor lock-in, incompatible semantics, incomplete exports	Rights to transfer, reuse, and delete data	Support portability by design through APIs, standards, and governance
Organisational interoperability	Aligns platform exchange with roles, responsibilities, and workflows	Service agreements, advisory protocols, workflow mappings, data-sharing arrangements	Stakeholder roles, decision responsibilities, process definitions	Misaligned incentives, unclear responsibilities, low trust	Accountability, transparency, benefit distribution	Design platform functions around real farm and advisory processes

Analytics and Decision-Support Integration

The analytics and AI layer of a smart farming platform transforms integrated agricultural data into descriptive, predictive, and prescriptive outputs. Machine-learning applications in agriculture demonstrate that algorithmic methods can support tasks such as crop monitoring, yield estimation, disease detection, irrigation planning, and machinery-related decision support when appropriate data are available and sufficiently prepared [16]. In the proposed architecture, AI modules should therefore be positioned after data ingestion, standardisation, semantic alignment, and governance controls rather than treated as independent tools detached from platform data quality.

Agricultural big-data analysis depends on pipelines that organise data collection, storage, preprocessing, modelling, interpretation, and reuse. Big-data research in agriculture shows that analytical value depends on the ability to manage diverse data sources and analytical practices across farm contexts [17]. For smart farming platforms, this means that analytics integration must include data fusion, provenance tracking, feature preparation, uncertainty handling, and interpretation pathways that connect model outputs to operational decisions.

Decision-support systems form the bridge between analytics outputs and farm action. Agriculture 4.0 decision-support research shows that DSS design must address decision context, usability, system integration, and user interpretation rather than only computational capability [18]. A platform that predicts irrigation demand, disease risk, input requirements, or yield variation is incomplete unless those outputs are translated into recommendations, alerts, maps, scenarios, or advisory explanations that farmers and advisors can evaluate.

AI integration should remain auditable, human-centred, and sensitive to agricultural context. Interdisciplinary work on AI in agriculture indicates that intelligent systems must account for ethical, social, organisational, and domain-specific considerations rather than assuming that algorithmic outputs automatically improve decisions [19]. In a smart farming platform architecture, analytics modules should therefore include traceability, uncertainty communication, feedback capture, and mechanisms for farmer or advisor oversight.

Architectural Requirements for Smart Farming Platforms

Data governance is a core architectural requirement because farm data are generated through relationships among farmers, machinery providers, platform operators, advisors, cooperatives, researchers, and technology vendors. Research on farmers and smart farming data shows that data sharing is shaped by legal uncertainty, trust, control, and concerns about how data may be accessed or reused [20]. A reference architecture must therefore specify ownership, access rights, permissions, consent, retention, provenance, and permitted reuse rather than assuming that all integrated data are freely available for platform analytics.

Transparency and accountability are equally important because platform users need to understand how data are used and who benefits from data exchange. Work on trust, transparency, and benefit-sharing in smart farming shows that farmers may be reluctant to participate in digital systems when data-use practices are unclear or when benefits are unevenly distributed [21]. Smart farming platforms should therefore include user-visible governance functions, audit trails, benefit-sharing logic, explainable data-use policies, and mechanisms for correcting or contesting data errors.

Security, privacy, and access control must operate as cross-cutting architectural services. Security and privacy research in smart farming identifies risks associated with connected devices, data transmission, cloud services, access management, and sensitive farm information [22]. The architecture should embed authentication, authorisation, encryption, role-based access, secure API management, privacy safeguards, and monitoring across device, connectivity, storage, analytics, and decision-support layers.

Platform resilience also requires monitoring and feedback mechanisms that detect technical faults, cybersecurity threats, data-quality problems, and workflow breakdowns. Agricultural IoT security research shows that smart farming environments face threat surfaces across sensors, networks, devices, applications, and data services [23]. A robust architecture should therefore include anomaly monitoring, incident logging, device-status tracking, security updates, and feedback from users and field outcomes so that the platform can learn from operational experience without claiming automatic optimisation.

Proposed Reference Architecture

The proposed interoperable reference architecture links technical platform layers to farm-management workflows and governance responsibilities. FMIS reference architecture research supports the need to connect platform design with planning, recordkeeping, operational coordination, and decision processes, while smart farming data-management and analytics-platform research supports explicit layers for ingestion, storage, governance, analytics, and modular service integration [24–26]. On this basis, the architecture is organised as a layered system rather than a single database, dashboard, or analytics engine.

The lower layers consist of physical sensing and machinery, connectivity and edge computing, and data ingestion. The physical layer includes IoT sensors, soil systems, weather stations, farm machinery, yield monitors, variable-rate application records, remote sensing, FMIS records, and advisory inputs. The connectivity and edge layer manages device communication, local preprocessing, buffering, and context-aware routing. The data ingestion layer validates, cleans, timestamps, spatially references, and prepares data for platform use. Platform-selection research for precision farming

data analytics indicates that feasibility, modularity, scalability, and platform fit should be considered when designing or selecting such components [27].

The middle layers include API and integration services, data standardisation, semantic interoperability, storage, governance, security, privacy, and access control. The API layer enables controlled exchange among software modules, FMIS tools, advisory services, machinery providers, and analytics components. The semantic layer aligns field identifiers, crop terms, operations, prescriptions, observations, and recommendations across systems. Digital data-platform research for small farmers shows that platform usefulness depends on turning integrated data into decision-support functions that are accessible to users rather than remaining hidden in technical back-end systems [28].

The upper layers include analytics and AI, decision support and visualisation, farm-management workflow integration, stakeholder interfaces, and monitoring, feedback, and learning. The analytics layer supports data fusion, descriptive monitoring, predictive modelling, risk alerts, and advisory interpretation. The decision-support layer translates analytical outputs into maps, alerts, recommendations, scenarios, and dashboards. Digital twin research in smart farming supports the value of feedback loops that connect digital models, platform data, field conditions, and decisions over time [29].

The architecture should distribute functions across edge and cloud environments according to latency, connectivity, scalability, and operational needs. Edge-cloud smart farming platform research shows that some functions can benefit from local processing near field devices, while other services may require cloud-based storage, integration, analytics, and coordination [30]. The proposed architecture therefore avoids assuming that cloud or edge computing is inherently superior; instead, it treats edge-cloud coordination as a design choice shaped by farm context, data sensitivity, communication reliability, decision urgency, and implementation capacity.

Table 3 presents the proposed interoperable reference architecture for smart farming platforms by linking architectural layers to integration functions, governance needs, and decision-support outputs.

Table 3. Proposed Interoperable Reference Architecture for Smart Farming Platforms: Sensing and Machinery Layer, Connectivity Layer, Data Ingestion Layer, API Layer, Semantic Interoperability Layer, Governance Layer, Analytics Layer, Decision-Support Layer, and Farm Workflow Layer

Architecture layer	Core function	Primary data inputs	Key interoperability requirement	Security or governance requirement	Analytics contribution	Decision-support output
Physical sensing and machinery layer	Captures field, machine, environmental, and operational data	IoT sensors, soil sensors, weather stations, machinery telemetry, yield monitors, variable-rate records	Device identification, consistent timestamps, spatial referencing, equipment metadata	Device ownership, data-source authentication, protection against tampering	Provides raw observations for monitoring and modelling	Field-convergent evidence for operation and machinery
Connectivity and edge layer	Transfers data and performs local processing where needed	Sensor signals, machinery logs, local weather data, remote field observations	Communication protocols, gateway compatibility, edge-service interfaces	Secure transmission, gateway access control, local data protection	Enables local filtering, buffering, and preprocessing	Timely and local operational continuity, reduced dependency, continuous connectivity

Data ingestion layer	Converts incoming data into platform-ready information	Device streams, machine files, imagery layers, FMIS exports, advisory records	Schema validation, unit harmonisation, geospatial alignment, temporal alignment	Provenance capture, data-quality logging, ingestion permissions	Creates cleaned and structured datasets for analytics	Reliable inputs for alerts, dashboard reports
API and integration layer	Enables controlled software-to-software exchange	FMIS data, machinery records, sensor services, analytics services, advisory tools	Stable APIs, endpoint documentation, versioning, authentication	API permissions, audit logs, consent-aware data sharing	Allows analytics modules and external services to access required data	Connects advisory services, integrates dashboard services, interoperates
Data standardisation and semantic interoperability layer	Aligns formats, meanings, and relationships across systems	Field identifiers, crop codes, operation records, sensor metadata, recommendation terms	Shared vocabularies, semantic mappings, ontologies, standard data models	Stewardship of definitions, accountability for mappings, transparent transformation rules	Improves data fusion and model interpretability	Compares maps, allows recommendations, cross-system interpretation
Data storage and governance layer	Stores data while managing access, rights, provenance, and lifecycle	Historical sensor data, machinery records, imagery, FMIS records, advisory records	Data catalogues, metadata repositories, interoperable storage structures	Ownership rules, consent, retention, access rights, benefit-sharing, auditability	Provides governed data assets for analytics and reporting	Trusted records, traceability, reusable data history
Security, privacy, and access-control layer	Protects platform services, users, and data assets	User accounts, device identities, farm records, API requests, analytics outputs	Identity management across systems, role-based access, secure API integration	Authentication, authorisation, encryption, privacy safeguards, incident monitoring	Maintains trusted analytical access and protects sensitive inputs	Secure data services, controlled sharing, privacy-aware reporting
Analytics and AI layer	Produces descriptive, predictive, and prescriptive insights	Cleaned sensor data, weather data, soil data, imagery, machinery records, FMIS records	Access to standardised, contextualised, quality-checked datasets	Model governance, traceability, responsible data use, bias monitoring	Supports crop monitoring, risk prediction, input planning, forecasting, anomaly detection	Predictions, score recommendations, scenarios
Decision-support and visualisation layer	Translates analytics into user-facing outputs	Analytics outputs, advisory interpretation,	Consistent representation of maps, alerts, recommendations,	Explainability, user permissions, accountability for recommendations	Converts model results into actionable	Dashboards, alerts, prescriptions, suggest scouting practices

		maps, farm records, thresholds	uncertainty, and context		decision formats	manage scenarios
Farm-management workflow layer	Embeds platform outputs into operational routines	Crop plans, field tasks, machinery operations, advisory schedules, compliance records	Workflow mapping between FMIS, machinery systems, advisory tools, and platform services	Responsibility for decisions, record integrity, transparent task histories	Uses analytics within planning, execution, review, and adaptation cycles	Updated task record, decision advisory
User and stakeholder interface layer	Provides role-specific access and collaboration	Dashboards, advisory portals, mobile interfaces, reports, permissions	Interface consistency, role-based views, cross-platform access	Transparency, consent management, stakeholder accountability	Supports interpretation, communication, and collaborative decision-making	Farmer v advisor v cooper reports, relevant summaries
Monitoring, feedback, and learning layer	Tracks platform performance, data quality, decisions, and outcomes	User feedback, field outcomes, system logs, incident reports, model outputs	Feedback-loop integration across data repositories, models, and workflows	Audit trails, accountability, correction rights, incident response	Supports model refinement, quality improvement, and adaptive management	Learning, revise recommendations, improved quality

Figure 1 illustrates the proposed interoperable reference architecture for smart farming platforms, showing how data move from field-level systems through interoperability and governance layers into analytics, decision support, and farm-management workflows.

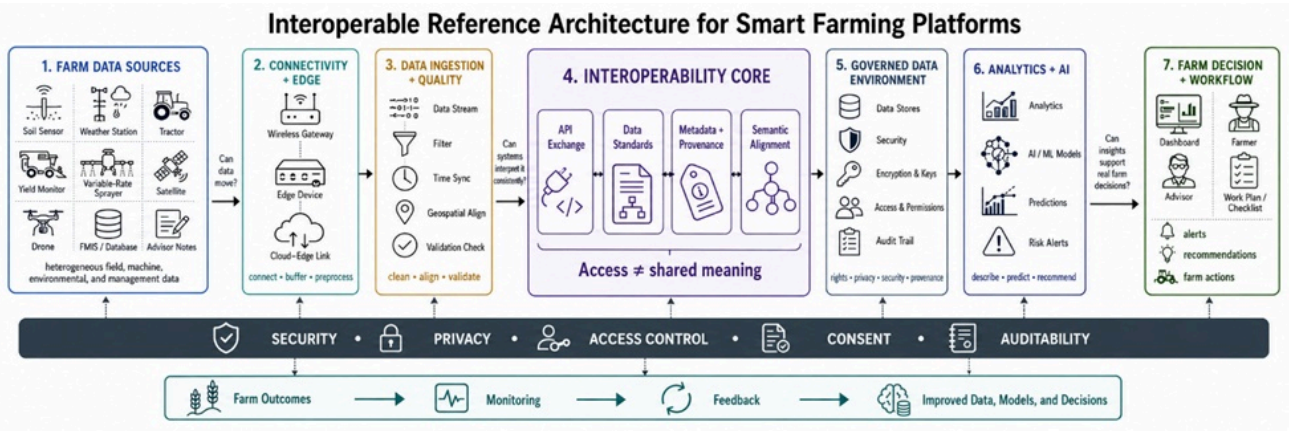


Figure 1. Interoperable Reference Architecture for Smart Farming Platforms. The figure presents a layered architecture linking field-level data sources, connectivity, data ingestion, APIs, semantic interoperability, data governance, analytics, decision support, and farm-management workflows. It shows how sensors, machinery, remote sensing systems, farm-management information systems, and advisory records can be integrated through modular and interoperable platform layers.

Alt-text description: A layered smart farming platform architecture diagram showing sensors, machinery, remote sensing, weather systems, soil data, and farm-management systems feeding into connectivity and data ingestion layers. These connect to API, metadata, semantic interoperability, governance, security, analytics, decision-support, dashboard, and farm workflow layers, with feedback loops from farm decisions back to field systems.

Practical Implications and Future Research

For platform developers, the proposed architecture highlights the need to design smart farming systems as modular integration environments rather than closed applications. API gateways, ingestion services, semantic mappings, storage repositories, governance services, analytics modules, and workflow interfaces should be designed with clear responsibilities and adaptable interfaces. The architecture can help developers connect API-mediated integration, interoperability architecture, FMIS reference architecture, data-management services, and analytics-platform functions without collapsing these functions into a single undifferentiated platform component [12].

For machinery manufacturers, FMIS providers, sensor companies, advisors, cooperatives, and farmers, the architecture clarifies where collaboration is required. Machinery providers must support interpretable operational records, FMIS providers must connect records and workflows, advisors must translate analytics into context-sensitive recommendations, and cooperatives or data stewards may help coordinate governance arrangements. Data ownership, trust, transparency, benefit sharing, security, and privacy should be treated as practical design responsibilities because they shape whether users can legitimately and confidently participate in platform-based data exchange [20-23].

Future research should empirically examine how the proposed architecture performs across farm types, production systems, platform ecosystems, and governance arrangements. Important research needs include cross-platform interoperability testing, API governance models, semantic standards for agricultural operations, farmer-centred interface design, edge-cloud coordination, analytics explainability, cybersecurity monitoring, data-quality assessment, and decision-workflow integration. Decision-support research, responsible AI scholarship, platform-selection research, digital-platform studies, digital twin research, and edge-cloud platform work all suggest that future studies should evaluate not only technical integration but also usability, accountability, adaptability, and the fit between platform outputs and farm decisions [18-19, 27-30].

Conclusion

This article proposed an interoperable reference architecture for smart farming platforms that connects field-level data sources, machinery systems, farm-management information systems, APIs, data standards, semantic interoperability, governance, analytics, decision support, and farm workflows. The central argument is that smart farming platform integration requires more than data transfer or dashboard aggregation: it depends on layered interoperability, contextual metadata, semantic alignment, secure and transparent governance, modular analytics, user-centred decision support, and feedback mechanisms that connect decisions back to farm realities. The architecture offers a structured design logic for researchers, developers, machinery manufacturers, FMIS providers, advisors, cooperatives, farmers, and policymakers while recognising that successful implementation depends on data quality, governance capacity, usability, institutional support, and adaptation to local farm contexts.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 09 Jan 2024

Revised: 08 Mar 2024

Accepted: 17 Apr 2024

Published online: 25 November 2024

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big data in smart farming -a review. *Agric Syst.* 2017;153:69-80.
<https://doi.org/10.1016/j.agsy.2017.01.023>.
- Klerkx L, Jakku E, Labarthe P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. *NJAS Wagening J Life Sci.* 2019;90-91:100315.
<https://doi.org/10.1016/j.njas.2019.100315>.
- Bacco M, Barsocchi P, Ferro E, Gotta A, Ruggeri M. The digitisation of agriculture: A survey of research activities on smart farming. *Array (N Y).* 2019;3-4:100009.
<https://doi.org/10.1016/j.array.2019.100009>.
- Verdouw C, Sundmaecker H, Tekinerdogan B, Conzon D, Montanaro T. Architecture framework of IoT-based food and farm systems: A multiple case study. *Comput Electron Agric.* 2019;165:104939.
<https://doi.org/10.1016/j.compag.2019.104939>.
- Moysiadis V, Sarigiannidis P, Vitsas V, Khelifi A. Smart farming in Europe. *Comput Sci Rev.* 2021;39:100345.
<https://doi.org/10.1016/j.cosrev.2020.100345>.
- Saiz-Rubio V, Rovira-Más F. From smart farming towards Agriculture 5.0: A review on crop data management. *Agronomy.* 2020;10(2):207.
<https://doi.org/10.3390/agronomy10020207>.
- Javaid M, Haleem A, Singh RP, Suman R. Enhancing smart farming through the applications of Agriculture 4.0 technologies. *Int J Intell Netw.* 2022;3:150-64.
<https://doi.org/10.1016/j.ijin.2022.09.004>.

Tzounis A, Katsoulas N, Bartzanas T, Kittas C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst Eng.* 2017;164:31-48.
<https://doi.org/10.1016/j.biosystemseng.2017.09.007>.

Elijah O, Rahman TA, Orikumhi I, Leow CY, Hindia MHDN. An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges. *IEEE Internet Things J.* 2018;5(5):3758-73.
<https://doi.org/10.1109/JIOT.2018.2844296>.

Navarro E, Costa N, Pereira A. A systematic review of IoT solutions for smart farming. *Sensors (Basel).* 2020;20(15):4231.
<https://doi.org/10.3390/s20154231>.

Tummers J, Kassahun A, Tekinerdogan B. Obstacles and features of farm management information systems: A systematic literature review. *Comput Electron Agric.* 2019;157:189-204.
<https://doi.org/10.1016/j.compag.2018.12.044>.

Bazzi CL, Jasse EP, Graziano Magalhães PS, Michelon GK, de Souza EG, Schenatto K, et al. AgDataBox API – integration of data and software in precision agriculture. *SoftwareX.* 2019;10:100327.
<https://doi.org/10.1016/j.softx.2019.100327>.

Bahlo C, Dahlhaus P, Thompson H, Trotter M. The role of interoperable data standards in precision livestock farming in extensive livestock systems: A review. *Comput Electron Agric.* 2019;156:459-66.
<https://doi.org/10.1016/j.compag.2018.12.007>.

Zeginis D, Kalampokis E, Palma R, Atkinson R, Tarabanis K. A semantic meta-model for data integration and exploitation in precision agriculture and livestock farming. *Semant Web.* 2024;15(4):1165-93.
<https://doi.org/10.3233/SW-233156>.

Urdu D, Berre AJ, Sundmaecker H, Rilling S, Roussaki I, Marguglio A, et al. Aligning interoperability architectures for digital agri-food platforms. *Comput Electron Agric.* 2024;224:109194.
<https://doi.org/10.1016/j.compag.2024.109194>.

Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: A review. *Sensors (Basel).* 2018;18(8):2674.
<https://doi.org/10.3390/s18082674>.

Kamilaris A, Kartakoullis A, Prenafeta-Boldú FX. A review on the practice of big data analysis in agriculture. *Comput Electron Agric.* 2017;143:23-37.
<https://doi.org/10.1016/j.compag.2017.09.037>.

Zhai Z, Martínez JF, Beltran V, Martínez NL. Decision support systems for agriculture 4.0: Survey and challenges. *Comput Electron Agric.* 2020;170:105256.
<https://doi.org/10.1016/j.compag.2020.105256>.

Ryan M, Isakhanyan G, Tekinerdogan B. An interdisciplinary approach to artificial intelligence in agriculture. *NJAS Impact Agric Life Sci.* 2023;95(1):2168568.
<https://doi.org/10.1080/27685241.2023.2168568>.

Wiseman L, Sanderson J, Zhang A, Jakku E. Farmers and their data: An examination of farmers' reluctance to share their data through the lens of the laws impacting smart farming. *NJAS Wagening J Life Sci.* 2019;90-91:100301.
<https://doi.org/10.1016/j.njas.2019.04.007>.

Jakku E, Taylor B, Fleming A, Mason C, Fielke S, Sounness C, et al. If they don't tell us what they do with it, why would we trust them? Trust, transparency and benefit-sharing in smart farming. *NJAS Wagening J Life Sci.* 2019;90-91:100285.
<https://doi.org/10.1016/j.njas.2018.11.002>.

Gupta M, Abdelsalam M, Khorsandroo S, Mittal S. Security and privacy in smart farming: Challenges and opportunities. *IEEE Access*. 2020;8:34564-84.

<https://doi.org/10.1109/ACCESS.2020.2975142>.

Demestichas K, Peppes N, Alexakis T. Survey on security threats in agricultural IoT and smart farming. *Sensors (Basel)*. 2020;20(22):6458.

<https://doi.org/10.3390/s20226458>.

Tummers J, Kassahun A, Tekinerdogan B. Reference architecture design for farm management information systems: A multi-case study approach. *Precis Agric*. 2021;22(1):22-50.

<https://doi.org/10.1007/s11119-020-09728-0>.

Krisnawijaya NNK, Tekinerdogan B, Catal C, van der Tol R. Reference architecture design for developing data management systems in smart farming. *Ecol Inform*. 2024;81:102613.

<https://doi.org/10.1016/j.ecoinf.2024.102613>.

Krisnawijaya NNK, Tekinerdogan B, Catal C, van der Tol R. Data analytics platforms for agricultural systems: A systematic literature review. *Comput Electron Agric*. 2022;195:106813.

<https://doi.org/10.1016/j.compag.2022.106813>.

Krisnawijaya NNK, Tekinerdogan B, Catal C, van der Tol R. Multi-criteria decision analysis approach for selecting feasible data analytics platforms for precision farming. *Comput Electron Agric*. 2023;209:107869.

<https://doi.org/10.1016/j.compag.2023.107869>.

Borrero JD, Mariscal J. A case study of a digital data platform for the agricultural sector: A valuable decision support system for small farmers. *Agriculture*. 2022;12(6):767.

<https://doi.org/10.3390/agriculture12060767>.

Verdouw C, Tekinerdogan B, Beulens A, Wolfert S. Digital twins in smart farming. *Agric Syst*. 2021;189:103046.

<https://doi.org/10.1016/j.agry.2020.103046>.

Zamora-Izquierdo MA, Santa J, Martínez JA, Martínez V, Skarmeta AF. Smart farming IoT platform based on edge and cloud computing. *Biosyst Eng*. 2019;177:4-17.

<https://doi.org/10.1016/j.biosystemseng.2018.10.014>.