

REVIEW

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Digital Twins in Smart Farming: A Scoping Review of Architectures, Enabling Technologies, Applications, and Research Gaps

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Abstract

Digital twins are increasingly discussed as a next step in smart farming because they promise to connect physical agricultural systems with digital representations, sensor data, simulation models, analytics, and decision-support functions. However, the agricultural literature remains uneven in how it defines, architects, enables, and applies digital twins across crop, livestock, greenhouse, irrigation, and farm-management systems. This original scoping review maps the peer-reviewed literature on digital twins in smart farming with attention to architecture types, enabling technologies, data requirements, application domains, implementation challenges, and research gaps. The review follows a scoping logic rather than an effect-estimation or performance-benchmarking design: it charts how studies conceptualize digital twins, distinguishes full or emerging digital twin capability from static models and monitoring dashboards, and classifies evidence by architecture, technology, data pipeline, analytics function, feedback mechanism, implementation stage, and limitation. The synthesis shows that agricultural digital twins are commonly positioned as cyber-physical and decision-support infrastructures that may combine IoT sensing, remote sensing, machinery and environmental data, cloud or edge computing, simulation, AI analytics, visualization, and farm-management interfaces. Application clusters are strongest in controlled-environment agriculture, irrigation and water management, crop monitoring, aquaponics, livestock monitoring, greenhouse visualization, and emerging optimization or automation settings. Across the mapped literature, the main contribution is a structured classification of digital twin architectures and application patterns while preserving conceptual caution: real-time data, AI prediction, or visualization alone does not create a digital twin. The review identifies future research needs in architecture standardization, semantic interoperability, field validation, real-time updating, uncertainty communication, data governance, farmer-centered usability, scalability, and sustainability assessment.

Keywords Precision agriculture, Smart farming, Digital twin, IoT, Scoping review, Cyber-physical systems

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Introduction

Digital twins have entered smart farming as a way to connect physical agricultural entities with digital representations that can be updated through data streams, interpreted through models, and used to support decisions. In agricultural settings, this concept is broader than a static digital model because it normally involves a physical system, a virtual representation, a data connection, model updating, analytics or simulation, and some form of feedback to management or operations [1–

3]. This distinction is important because many digital agriculture systems use sensors, dashboards, remote sensing, or prediction tools, but not all of them meet the conceptual threshold of a digital twin.

The relevance of digital twins in smart farming reflects the broader shift toward cyber-physical and data-intensive agriculture. Agricultural production increasingly depends on sensing, connected devices, automation, AI-enabled analytics, and decision-support environments that can represent changing field, greenhouse, livestock, irrigation, and farm-operational conditions [4]. Within this transformation, the digital twin paradigm is best understood as a systems-integration concept rather than as a single technology, software platform, or universal model.

A scoping review is needed because the agricultural digital twin literature is expanding across several partially connected domains, including smart-farming infrastructure, controlled-environment agriculture, crop monitoring, livestock systems, irrigation, aquaponics, edge-cloud computing, reinforcement learning, and sustainability-oriented decision support. The field includes conceptual frameworks, review papers, prototype-oriented studies, simulation environments, architecture proposals, and domain-specific implementations. As a result, a generic narrative review would risk flattening important differences among architecture types, levels of physical-digital coupling, data requirements, analytics functions, and implementation maturity [3].

The aim of this review is to map how digital twins are conceptualized, architected, enabled, and applied across smart farming systems. The mapping questions are: how are digital twins defined and positioned in smart farming literature; what architecture types are used; which enabling technologies and data sources support them; which application domains are most commonly addressed; how do studies connect digital twins to monitoring, simulation, prediction, optimization, decision support, or automation; and what limitations and research gaps remain for robust, interoperable, farmer-centered digital twin systems?

Digital Twins as Smart Farming Infrastructure

In the agricultural context, digital twins may be understood as smart-farming infrastructure when they integrate physical production systems, data acquisition, computational models, analytics, visualization, and management feedback. This infrastructure framing is important because digital twins are not simply digital replicas placed beside farm systems; they depend on the organized coupling of data flows, model behavior, decision services, and context-specific operational goals. Sustainability-oriented discussions of agricultural digital twins therefore require careful interpretation because potential environmental or resource-management benefits depend on data quality, system integration, validation, and local production conditions [5].

Digital twin infrastructure also depends on enabling layers that are already common in smart agriculture, including IoT sensors, communication networks, cloud or edge services, AI analytics, and user-facing decision tools. Reviews of smart-agriculture digital twin implementation show that these components are necessary but not sufficient: a sensor network can supply data, a dashboard can visualize measurements, and an AI model can predict outcomes, yet a digital twin requires these components to be organized into a physical-digital system with updating and decision relevance [6]. This is why the review treats IoT, AI, and visualization as enabling technologies rather than as automatic evidence that a full digital twin exists.

Digital twins are also infrastructural because they require orchestration across heterogeneous data sources, models, software services, domain knowledge, and decision workflows [7]. In smart farming, this orchestration may involve soil and climate data, crop or animal measurements, machinery records, remote sensing, weather data, farm-management information systems, simulation models, and advisory interfaces. The practical value of a digital twin depends on whether these elements can be combined into a coherent representation of the agricultural system being managed, rather than remaining isolated data streams or disconnected analytical tools.

This review therefore distinguishes digital twins from related concepts that often overlap with them. A digital model may represent a crop, animal, greenhouse, or irrigation system without being continuously updated from physical data. A simulation model may test scenarios without being connected to ongoing farm operations. A monitoring dashboard may display sensor data without predictive, simulation, or feedback capability. A farm-management information system may organize records without maintaining a dynamic digital representation of a physical process. Digital twins may include elements of all these systems, but they require stronger physical-digital coupling and decision-oriented updating than any one of them alone.

Review Scope and Mapping Approach

This article follows a scoping review logic designed to map the breadth and structure of the literature rather than to estimate effect sizes, compare intervention outcomes, or rank technologies by performance. The scope includes peer-reviewed journal articles that address digital twin definitions, architectures, enabling technologies, data requirements, agricultural applications, decision-support functions, implementation barriers, or research gaps in smart farming and related agricultural systems. Sustainability-oriented studies were included when they directly discussed digital twins or digital-twin-relevant agricultural systems and when their claims could be mapped cautiously as evidence clusters, open challenges, or future directions rather than assumed outcomes [8].

Eligibility focused on journal articles within the approved search window that included a DOI and had enough information to classify the paper by digital twin relevance, agricultural domain, architecture type, enabling technology, data source, analytics or simulation function, feedback mechanism, implementation stage, limitation, and research gap. Studies were excluded when they used “digital twin” only superficially, lacked agricultural relevance, focused only on generic AI, IoT, remote sensing, or simulation without digital twin relevance, or could not be mapped to the review categories. Greenhouse horticulture was treated as a distinct application cluster because controlled environments often permit denser sensing, more structured model updating, clearer visualization needs, and tighter links between monitoring and control than many open-field settings [9].

The search and screening process was conducted as a curated scoping selection rather than a full PRISMA-ScR count-based search. Candidate literature was identified across scholarly databases and publisher platforms, including ScienceDirect, IEEE Xplore, MDPI, ACS, Nature/Springer, and other relevant journal sources. Part 1 generated a verified candidate pool of 48 records and a final included set of 32 peer-reviewed journal articles, but it did not generate transparent duplicate-removal counts, title-abstract exclusion counts, full-text exclusion counts, or exclusion-reason frequencies. For this reason, the manuscript does not claim PRISMA-ScR compliance and does not invent a count-based PRISMA flow.

Data charting classified each included article by digital twin type, agricultural domain, architecture type, physical system represented, data sources, enabling technologies, analytics or simulation function, feedback or control mechanism, application purpose, implementation stage, main limitation, and research gap. Crop-monitoring studies were charted as a separate cluster because the literature often links digital twins to sensing, remote monitoring, environmental data, prediction, and partial decision support, while only some studies demonstrate stronger physical-digital updating or operational feedback [10]. **Table 1** summarises the scoping review mapping framework used to classify digital twin studies in smart farming.

Table 1. Scoping Review Mapping Framework for Digital Twins in Smart Farming: Architecture Type, Enabling Technologies, Data Requirements, Application Domain, Analytics Function, Feedback Mechanism, Implementation Stage, and Research Gap Category

Mapping dimension	Definition	Coding categories	Information extracted	Reason for inclusion	Example interpretation	Limitation of the category
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Digital twin definition	How the article defines or positions a digital twin	Explicit DT definition; partial DT; DT-like architecture; enabling concept	Definition language, physical-digital coupling, updating logic	Prevents treating every model or dashboard as a DT	A crop model with no live updating is coded as a model, not a full DT	Some papers use DT language inconsistently
Architecture type	How the DT system is structurally organized	Cyber-physical; IoT-enabled; simulation-based; data-driven; hybrid model-data; cloud-edge; decision-support	Physical layer, data layer, model layer, analytics layer, interface layer	Identifies how DTs are built and compared	A greenhouse DT may combine sensing, simulation, visualization, and control	Architecture details are sometimes incomplete
Enabling technologies	Technologies supporting the DT	IoT; remote sensing; machinery data; cloud; edge; AI; simulation; data fusion; visualization	Sensors, platforms, models, algorithms, interfaces	Separates enabling tools from the DT concept itself	IoT supplies data but does not alone constitute a DT	Technology labels may be broad or underspecific
Data requirements	Data needed for model updating and decision support	Sensor data; environmental data; soil data; crop data; animal data; machinery data; management records	Data source, frequency, integration method, quality issue	DT fidelity depends on relevant and reliable data	Irrigation DTs require soil-water, weather, and operational data	Many papers do not report data quality in detail
Application domain	Agricultural system or decision context	Crop; livestock; greenhouse; irrigation; aquaponics; vertical farm; soil/climate; farm operations	Production system, management problem, decision target	Maps evidence clusters across smart farming	Controlled-environment studies form a strong cluster	Some applications overlap across domains

Analytics function	Computational role of the DT	Monitoring; simulation; prediction; optimization; anomaly detection; decision support; automation	Analytical method, model purpose, output type	Clarifies whether the DT is descriptive, predictive, prescriptive, or control-oriented	A Q-learning vertical-farm DT is coded as optimization-oriented	Papers may claim analytic functions without full validation
Feedback mechanism	How digital outputs influence decisions or operations	Advisory feedback; dashboard feedback; semi-automated control; autonomous control; not clearly reported	Recommendation pathway, control loop, human role	Feedback distinguishes DTs from passive visualization	A DSS recommending irrigation actions is advisory feedback	Feedback is often described conceptually rather than operationally
Implementation stage	Maturity of the reported DT	Conceptual; review; architecture proposal; prototype; simulation; applied study; field implementation	Evidence type, deployment setting, validation status	Avoids overstating maturity	A ROS-Gazebo greenhouse system is simulation/prototype-oriented	Boundaries between prototype and implementation may be unclear
Research-gap category	Main limitation or future need	Validation; interoperability; scalability; data quality; usability; governance; integration; sustainability assessment	Reported limitation, unresolved issue, future work	Supports future research synthesis	A greenhouse sensor-selection paper may highlight microclimate data fidelity	Some gaps are inferred from article scope rather than directly stated

Digital Twin Architectures

The scoped literature shows that agricultural digital twin architectures are typically organized around layered relationships among the physical system, data-acquisition infrastructure, digital representation, analytics or simulation layer, visualization interface, and decision-support pathway. In controlled-environment agriculture, architecture proposals often begin with the production environment as the physical referent and then connect environmental sensing, crop-system representation, and optimization-oriented services that may support productivity-oriented decisions [11]. This architecture

pattern is particularly visible in greenhouse, vertical farming, hydroponic, and aquaponic settings, where boundaries of the physical system are easier to define than in many open-field environments.

A broader agricultural architecture pattern treats digital twins as layered cyber-physical systems in which physical farm entities are linked to virtual models through data exchange and service functions. Such architectures usually include a physical layer, data-communication layer, virtual-model layer, analytics layer, and application layer for decision support or management services [12]. This layered pattern is useful for scoping because it separates enabling infrastructure from digital twin functionality: sensors and connectivity enable data exchange, models and analytics enable interpretation, and user or control interfaces enable feedback to agricultural decisions.

Decision-support architectures are especially prominent in aquaponics and related controlled food-production systems. In an urban aquaponics digital twin, decision support is created by connecting sensed system states, digital representations, and management-oriented reasoning so that users can interpret system behavior and act on recommendations [13]. This type of architecture is important because it demonstrates that agricultural digital twins may be most practically valuable when they support human and managerial decisions, rather than when they are presented as fully autonomous systems.

Hydroponic and aquaponics-factory studies further illustrate hybrid architecture requirements, including physical-digital grow-bed representation, water-quality and environmental data acquisition, interface development, data integration, and potential feedback to operations [14]. At a larger production-system scale, aquaponics factory digital twins show that architecture design must also address integration across biological, hydraulic, environmental, and operational subsystems, making validation and interoperability central research needs rather than secondary implementation details [15].

Enabling Technologies and Data Requirements

Digital twins in smart farming depend on enabling technologies that supply, integrate, model, analyse, and communicate agricultural data. Big-data infrastructures, IoT sensing, and AI-enabled automation provide important foundations for digital twin development, but each must be interpreted carefully because none of them independently constitutes a digital twin [16–18]. A smart-farming big-data system can aggregate heterogeneous farm records, sensor streams, spatial data, machinery logs, and weather information, yet it becomes digital-twin-relevant only when these data contribute to an updated representation of a physical agricultural system and support simulation, prediction, decision reasoning, or feedback.

Reliable sensing and connectivity are therefore foundational data requirements. Agricultural IoT technologies support data acquisition from soil sensors, environmental sensors, irrigation devices, livestock wearables, machinery systems, greenhouse controllers, and other connected farm assets [19]. However, the review scope indicates that agricultural digital twins require more than data availability: they need appropriate temporal resolution, spatial relevance, data quality control, contextual interpretation, and mechanisms for updating digital representations. Poorly integrated sensor networks may improve monitoring but still fall short of digital twin functionality when data are not connected to models, analytics, or decisions.

Cloud and edge computing appear as important architectural enablers because agricultural digital twins may need to process high-volume or near-real-time data while remaining usable in farm environments. Edge-cloud architectures can support crop monitoring and detection when physical data streams are connected to analytics and user-facing services, as shown in recent tomato-monitoring digital twin work [20]. This pattern is especially relevant for smart farming because data may be generated in distributed field, greenhouse, or machinery environments where connectivity, latency, computing cost, and local decision needs differ substantially across production contexts.

The data requirements identified across the scoped literature include physical-system measurements, environmental observations, operational records, remote-sensing inputs, crop or animal status indicators, and management data. These

data must be linked to simulation models, AI analytics, visualization tools, and decision-support interfaces in ways that preserve domain meaning. Interoperability is therefore not only a software concern but also a semantic and agronomic requirement: soil moisture, greenhouse temperature, animal movement, irrigation timing, crop imagery, and machinery activity must be represented in forms that can be interpreted by both computational models and farm decision-makers.

Table 2 compares enabling technologies and data requirements reported across digital twin studies in smart farming.

Table 2. Enabling Technologies and Data Requirements for Digital Twins in Smart Farming: IoT Sensors, Remote Sensing, Machinery Data, Cloud and Edge Computing, Simulation Models, AI Analytics, Data Fusion, Interoperability, and Visualization

Enabling technology or data component	Role in digital twin development	Typical agricultural data sources	Architecture layer supported	Decision-support function	Implementation requirement	Common limitation	Finding
IoT sensors	Provide physical-system measurements for digital updating	Soil moisture, temperature, humidity, water quality, animal movement, greenhouse climate	Physical and data-acquisition layers	Monitoring, alerts, state estimation	Reliable sensing, calibration, connectivity, maintenance	Sensor drift, missing data, limited spatial coverage	Quantitative structural parameters
Remote sensing	Adds spatial and temporal observation of crops and environments	Satellite imagery, UAV imagery, multispectral or thermal observations	Data-acquisition and data-fusion layers	Crop monitoring, stress detection, spatial decision support	Georeferencing, temporal alignment, image preprocessing	Cloud cover, revisit frequency, resolution mismatch	Seasonal insights
Machinery data	Connects operations and field activities to digital representations	Tractor logs, implement data, input application records, machine telemetry	Operational data layer	Farm operations, input optimization, traceability	Data access, standard formats, platform integration	Proprietary formats and fragmented machinery ecosystems	Advances in digital twins
Weather and climate data	Provides environmental context for model updating and prediction	Weather stations, forecasts, greenhouse climate records, climate databases	Context and simulation layers	Irrigation, crop-risk assessment, disease-risk support	Local relevance, temporal resolution, uncertainty handling	Coarse spatial resolution or forecast uncertainty	Uncertainty aware simulation
Soil data	Represents below-ground	Soil moisture, texture,	Physical-state and	Irrigation, fertility, crop	Sampling design, sensor	High spatial heterogeneity	Scale

	production conditions	nutrients, salinity, pH, temperature	simulation layers	growth support	calibration, spatial mapping	and expensive dense sensing	d u rep
Cloud computing	Supports storage, analytics, and platform-level integration	Multisource farm data, model outputs, historical records	Platform and analytics layers	Large-scale analytics, visualization, farm-management integration	Secure data transfer, scalable architecture, governance rules	Connectivity dependence and data-governance concerns	S ar th s pr
Edge computing	Processes data near the farm system	Greenhouse sensor streams, crop images, local machine data	Edge analytics and response layer	Near-real-time monitoring, detection, local decision support	Local processing hardware, model deployment, maintenance	Resource limits and deployment complexity	e co f far
Simulation models	Represent system behaviour and scenario responses	Crop models, water-balance models, greenhouse climate models, aquaponics process models	Digital representation and analytics layers	What-if analysis, prediction, optimization support	Model calibration, validation, domain adaptation	Limited transferability across contexts	S val hy a
AI analytics	Extracts patterns, predictions, and classifications	Images, sensor streams, animal behaviour data, crop and climate records	Analytics and decision-support layers	Prediction, anomaly detection, optimization, automation support	Training data, validation, explainability, monitoring	Data bias, opacity, weak field validation	e u av D
Data fusion	Integrates heterogeneous data into coherent representations	Sensor, remote-sensing, machinery, weather, soil, crop, and management data	Integration layer	State estimation, context-aware decisions, model updating	Semantic alignment, temporal synchronization, quality control	Inconsistent formats and missing metadata	int da a pi a
Interoperability	Allows systems, models, and platforms to exchange meaningful data	FMIS data, machinery data, sensor networks, model outputs	Cross-layer architecture requirement	Cross-platform decision support and	Standards, APIs, ontologies, governance agreements	Fragmented platforms and proprietary systems	s inte a

				lifecycle management			al
Visualization and interfaces	Makes DT states and recommendations interpretable to users	Dashboards, VR environments, maps, alerts, model outputs	User-interface and feedback layer	Human interpretation, decision confidence, advisory feedback	User-centered design, readable outputs, contextual explanation	Risk of passive dashboards without feedback logic	fa ce vi ar

Applications Across Smart Farming Systems

Irrigation and water management are among the clearest application areas for agricultural digital twins because they can connect soil-water status, environmental conditions, crop needs, irrigation infrastructure, and management decisions. Digital twin irrigation systems may support water-saving decisions when data streams and decision logic are connected to a physical irrigation context [21]. Nevertheless, these systems should be interpreted as decision-support infrastructures rather than as automatic guarantees of water savings, because effectiveness depends on sensing quality, model calibration, crop context, farm constraints, and implementation conditions.

Crop-monitoring and crop-management applications show how digital twins may support more individualized or context-aware production decisions. Work on mandarin digital twins demonstrates the potential for crop-specific digital representations that can connect plant or orchard information with predictive analysis and management support [22]. This evidence cluster is important because it moves beyond generic field monitoring toward more precise representations of crop condition, although broader transferability across crops, regions, production systems, and data environments still requires further study.

Greenhouse and controlled-environment agriculture applications show a relatively strong fit with digital twin logic because the physical system can be bounded, monitored, modelled, visualized, and adjusted more readily than many open-field systems. Virtual reality-based greenhouse digital twins highlight the importance of visualization and human interaction, showing that the user interface is not a decorative layer but part of how system states and digital representations become actionable for managers, advisors, and operators [23]. Greenhouse digital twins may therefore support monitoring, scenario interpretation, training, and decision support, but they still require evidence on usability and operational value.

Livestock and robotic greenhouse applications expand the scope of digital twins beyond crop monitoring and irrigation. Livestock digital twins may use animal sensor data, behavioural indicators, computer vision, and analytics to support monitoring, welfare assessment, and farmer or veterinary decision-making, but they also raise ethical, governance, and interpretation challenges [24]. Robotic greenhouse digital twin environments show how simulation and deep learning may support automation research, yet simulation-based performance should not be treated as equivalent to validated field deployment [25]. These examples reinforce the need to classify applications by implementation stage and feedback maturity.

Scoping Synthesis

The scoped literature shows that digital twins in smart farming are concentrated around a small number of evidence clusters rather than evenly distributed across all agricultural domains. Water-management studies form a visible cluster because irrigation decisions can be connected to sensor data, environmental context, water-demand reasoning, and sustainability-oriented management goals [26]. This cluster is promising for scoping synthesis because it connects data requirements, decision support, and resource management, but the literature still requires stronger evidence on validation, interoperability, and implementation across diverse farm types and climatic conditions.

Optimization and adaptive decision-making are emerging themes, particularly where digital twins are combined with reinforcement learning or other prescriptive analytics. Reinforcement-learning-based digital twins may support adaptive control and optimization, but the agricultural evidence remains early-stage and requires careful treatment because safety, explainability, data availability, and field validation remain unresolved [27]. This suggests that optimization-oriented digital twins should be framed as a future-facing research direction unless the reviewed study provides clear operational evidence.

Controlled-environment agriculture, including vertical farms and greenhouses, offers another strong pattern because environmental variables, production schedules, and resource inputs can often be more tightly monitored and adjusted. Vertical-farm digital twins using Q-learning illustrate how data, simulation, and adaptive decision logic can be integrated for production-strategy optimization in controlled settings [28]. However, these systems should not be generalized uncritically to open-field agriculture, where weather exposure, spatial heterogeneity, machinery coordination, labour variability, and biological uncertainty create more complex modelling and feedback conditions.

A cross-cutting synthesis theme is that digital twin fidelity depends heavily on sensor selection, data quality, and the ability to represent spatial and temporal variability. Greenhouse microclimate studies show that sensor placement and heterogeneous local conditions can affect the quality of digital representations and the usefulness of monitoring outputs [29]. This insight extends beyond greenhouses: agricultural digital twins require not only more data but better-positioned, better-calibrated, better-integrated, and better-contextualized data.

Overall, the literature is best described as a mixed field of conceptual frameworks, reviews, architecture proposals, simulation-oriented studies, prototype systems, and selected applied demonstrations. The evidence is stronger for describing digital twin potential, architecture components, enabling technologies, and application clusters than for proving generalized productivity, sustainability, economic, or automation outcomes. Consequently, the scoping synthesis emphasizes mapping, classification, and conceptual boundary-setting rather than performance ranking.

Table 3 synthesizes the main architecture, technology, application, and research-gap patterns identified across the scoped digital twin literature.

Table 3. Scoping Synthesis of Digital Twins in Smart Farming: Architecture Patterns, Enabling Technologies, Application Domains, Implementation Stages, Limitations, and Research Gaps

Synthesis category	Dominant pattern in the literature	Representative digital twin function	Application domain	Data or technology dependency	Main implementation barrier	Research gap	
Conceptual definition	DTs are framed as physical-digital systems, but terminology varies	Clarifying distinction from models, dashboards, and DSS tools	Cross-cutting smart farming	Conceptual models, system boundaries, data-connection logic	Inconsistent use of “digital twin”	Lack of agricultural DT maturity criteria	
Cyber-physical architecture	Layered architectures link physical systems, data, models, analytics, and interfaces	Physical-digital coupling and system-state updating	Greenhouse, aquaponics, crop systems, farm operations	IoT, data platforms, simulation, visualization	Fragmented integration across layers	Limited architecture standardization	

IoT-enabled monitoring	Sensors provide real-time or near-real-time farm observations	Monitoring and state estimation	Soil, irrigation, greenhouse climate, livestock, machinery	Sensor networks, connectivity, calibration	Sensor drift, missing data, limited coverage	Weak data-quality reporting	Bu a p
Simulation-based twins	Models support scenario testing and system behaviour representation	What-if analysis and predictive reasoning	Greenhouse, irrigation, aquaponics, vertical farming	Simulation models, calibration data, domain expertise	Model transferability and validation	Limited field-calibrated simulation evidence	A m v
AI/data-driven twins	AI supports detection, prediction, classification, and optimization	Prediction, anomaly detection, adaptive decision support	Crop monitoring, robotics, livestock, vertical farming	Training data, computing resources, labelled observations	Opacity, bias, weak external validation	Limited explainability and uncertainty communication	I ex ur a
Edge-cloud architecture	Computing is distributed between local devices and cloud platforms	Near-real-time analytics and scalable storage	Tomato monitoring, greenhouse systems, distributed farm assets	Edge hardware, cloud infrastructure, data transfer	Connectivity, cost, maintenance, security	Few context-specific deployment studies	E rol c de
Visualization and human interaction	Interfaces translate digital representations into usable information	Dashboards, VR, decision interpretation	Greenhouses, farm management, training, advisory contexts	Visualization tools, user-interface design, contextual data	Passive visualization without decision feedback	Limited farmer-centered usability evidence	T ce ir wi an
Irrigation and water management	Strong application cluster around resource management	Irrigation scheduling and water-use decision support	Irrigation systems and water management	Soil-water data, weather data, models, sensors	Site-specific calibration and interoperability	Limited cross-context validation	I s ma
Controlled-environment agriculture	Strong fit because systems are bounded and sensor-rich	Monitoring, optimization, simulation, feedback	Greenhouse, hydroponics, aquaponics, vertical farms	Climate sensors, control systems, growth data, simulation	Transferability beyond specific facilities	Limited multi-site validation	Co arc c env
Livestock systems	Emerging cluster around animal	Behaviour monitoring, welfare support,	Livestock farming	Wearables, computer vision,	Ethics, data governance, animal variability	Limited animal-centered validation	I s

	monitoring and welfare	advisory decisions		physiological data, AI			livestock
Automation and robotics	Simulation environments support robotic and autonomous research	Robotic planning, grasping, simulated feedback	Greenhouse robotics and automation	Simulation platforms, AI, robot sensors, control systems	Simulation-to-reality gap	Limited operational closed-loop validation	Simulation-based research
Sustainability support	Sustainability is frequently discussed but often indirectly evidenced	Resource-use assessment and decision support	Irrigation, crop management, smart agriculture	Environmental data, models, sustainability indicators	Overstated benefits without validation	Weak outcome measurement	Literature-based sustainability assessment

Figure 1 illustrates the scoping synthesis map linking digital twin architectures, enabling technologies, smart farming applications, implementation barriers, and future research directions.

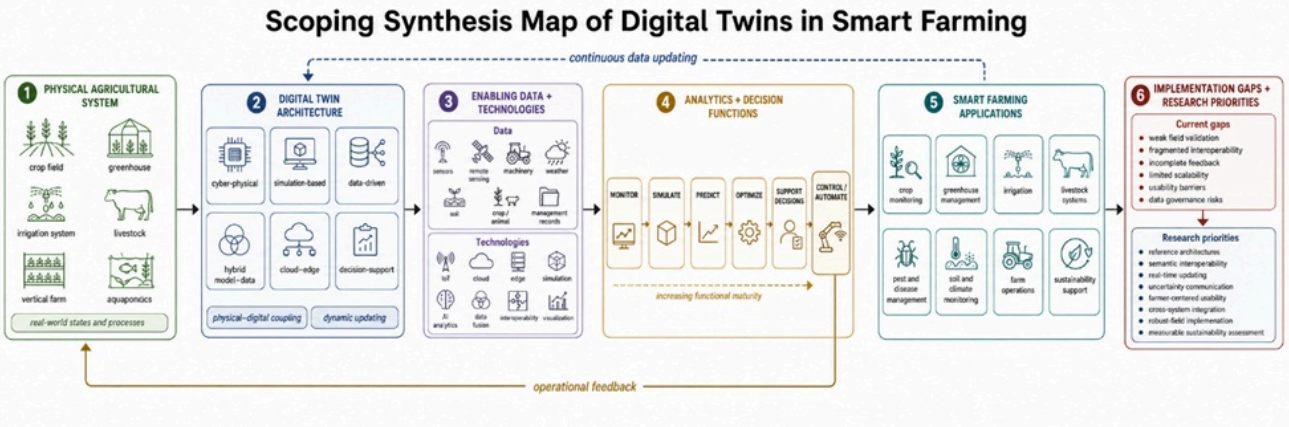


Figure 1. Scoping Synthesis Map of Digital Twins in Smart Farming. The figure integrates the main scoping review categories by linking architecture types, enabling technologies, agricultural data requirements, application domains, implementation barriers, and future research directions for digital twins in smart farming.

Alt-text description: A conceptual synthesis map showing digital twin architectures connected to enabling technologies, data requirements, smart farming applications, implementation barriers, and research gaps. Architecture types connect to IoT, remote sensing, data fusion, simulation, AI analytics, cloud and edge computing, visualization, decision support, crop systems, livestock systems, greenhouse systems, irrigation, monitoring, optimization, interoperability gaps, validation gaps, and future research priorities.

Research Gaps and Future Directions

The first research gap is conceptual and architectural clarity. Broad reviews of digital twins in agriculture and forestry indicate that the field still needs stronger validation, interoperability, scalability, data-quality management, and domain-specific integration [30]. Future studies should specify whether they present a conceptual digital twin, a partial digital twin, a digital twin-like architecture, a simulation environment, a monitoring dashboard, or an operational physical-digital system. Without this clarity, the literature risks overstating maturity and comparing systems that do not share the same technical or functional boundaries.

The second gap concerns interoperability, standardization, and complete feedback loops. Recent reviews of agricultural digital twin progress identify fragmented architectures, limited standardization, incomplete integration, and open issues in physical-digital feedback [31]. Future work should therefore prioritize semantic interoperability, reusable data models, cross-platform interfaces, and transparent architecture documentation. Agricultural digital twins will be difficult to scale if each system is built around isolated data structures, proprietary platforms, incompatible machinery formats, or domain-specific models that cannot be connected to broader farm-management workflows.

The third gap concerns farmer-centered implementation. Comprehensive reviews of agricultural digital twin technology point toward the need for robust, interoperable, validated, context-aware, and farmer-centered systems rather than universal one-size-fits-all architectures [32]. Future research should examine how farmers, advisors, veterinarians, greenhouse managers, irrigation specialists, and other users interpret digital twin outputs, manage uncertainty, and incorporate recommendations into real decisions. Visualization, explainability, trust, workload, local knowledge, and advisory relationships should be treated as core design concerns rather than as secondary interface features.

The fourth gap concerns validation, governance, and sustainability assessment. Digital twins may support monitoring, simulation, prediction, optimization, and decision support, but the literature does not justify broad claims that they automatically improve productivity, reduce environmental impacts, or eliminate human decision-making. Future studies should validate digital twin outputs under real production conditions, report uncertainty and data limitations, address data ownership and governance, evaluate lifecycle maintenance requirements, and connect sustainability claims to measurable assessment frameworks. Scoping evidence suggests that the field's next stage should move from promising architectures toward transparent, validated, interoperable, and usable digital twin ecosystems.

Conclusion

This scoping review mapped digital twins in smart farming by organizing the literature around definitions, architecture types, enabling technologies, data requirements, application domains, analytics functions, feedback mechanisms, implementation stages, limitations, and research gaps. The synthesis shows that digital twins have potential as smart-farming infrastructure when they connect physical agricultural systems with updated digital representations, simulation or analytics, visualization, and decision-support pathways. At the same time, the review emphasizes conceptual caution: sensors, dashboards, AI models, remote-sensing systems, and simulations do not become digital twins unless they are integrated into meaningful physical-digital and decision-oriented systems. The field now requires stronger architecture standardization, semantic interoperability, data governance, uncertainty communication, farmer-centered usability, field validation, scalability, and sustainability assessment before digital twins can be treated as mature infrastructure across diverse agricultural contexts.

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