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Digital twin integration with generative AI and foundation models for real-time precision agriculture and crop resilience

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Abstract
Digital Twins (DTs) are emerging as a foundational technology in precision agriculture, enabling real-time virtualization, prediction, and autonomous optimization of crop systems. This review synthesizes current advances in DT applications across three major frontiers: precision nutrient management, dynamic water use efficiency, and proactive stress and resilience management. We highlight how hybrid modelling frameworks combining mechanistic crop models, machine learning, deep reinforcement learning, and high-throughput phenotyping enhance predictive capability and operational decision-making. The paper also examines the critical roles of Explainable AI, federated learning, and edge cloud architectures in improving transparency, data sovereignty, and scalability. Persistent challenges remain in data standardization, interoperability, rural digital infrastructure, and workforce capacity. Future progress depends on integrating foundation models, biologically constrained simulations, and privacy-preserving learning protocols into next-generation DT systems. Together, these developments position DTs as a transformative engine for sustainable, efficient, and climate-resilient agriculture.

Keywords: Digital twins, artificial intelligence, machine learning, precision agriculture, one-way digital shadow

1. Introduction
The Paradigm Shift to AI-Enabled Digital Agriculture
1.1. Global Food Security and the Resource Efficiency Crisis
The agricultural sector globally faces an unprecedented confluence of challenges defined by resource scarcity and increasing demand. Projections indicate that agricultural production must increase by 25% to 70% by 2050 to sustain a world population anticipated to exceed 10 billion individuals (Zhang, 2025) [51]. This critical imperative for increased output is complicated by escalating environmental pressures, including climate change impacts, resource depletion, and evolving consumer preferences for sustainable products. Traditional farming methodologies, based largely on empirical experience and historical averages, are fundamentally incapable of addressing the high variability and complexity inherent in modern agricultural systems (Melesse, 2025) [32].

This scenario necessitates a fundamental shift toward Precision Agriculture (PA) strategies that move beyond mere localized monitoring to incorporate predictive, prescriptive, and autonomous control systems (Zhang, 2025) [51]. The successful management of key agricultural inputs nutrients and water requires technologies capable of optimizing consumption, improving resource efficiency, and enhancing crop resilience against both biotic and a-biotic threats (Melesse, 2025) [32]. The convergence of high-fidelity modeling and advanced data analytics, specifically through Digital Twins (DTs) and Artificial Intelligence (AI), provides the architectural framework necessary to simulate, predict, and optimize these complex, highly variable biological processes in real-time, thereby ensuring both farm productivity and ecological sustainability (Peladarinos, 2023) [35].

1.2. Defining the Nexus: Digital Twins, AI and Precision Agriculture

The Digital Twin concept serves as a virtual counterpart, replicating the characteristics and functionalities of tangible objects, processes, or entire systems within the digital space (Peladarinos, 2023) [35]. Crucially, an agricultural DT is a dynamic, continuously updated digital replica of a physical entity, such as a field or an irrigation system, integrating live data streams from sensors and external sources (Bautista, 2025) [4]. This continuous data exchange differentiates DTs from conventional simulations, which merely replicate what *could* happen to a product or process based on introduced parameters. In contrast, a DT replicates what *is actually happening* to a specific asset in the real world.

The efficacy of the DT architecture is critically dependent on Artificial Intelligence. AI functions as the advanced analytical engine, automatically processing the massive, diverse, and high-quality data generated by the DT system. It is responsible for translating raw data into actionable intelligence, providing sophisticated insights, generating real-time predictions, and suggesting optimal strategies to prevent potential issues and enhance management decisions (Peladarinos, 2023) [35].

This paper systematically reviews the integration of DTs and AI, focusing on their capacity to deliver prescriptive insights across the three critical frontiers of sustainable intensification: precision nutrient management, dynamic water management, and proactive crop stress management.

1.3. Review Objectives, Structure, and Key Contributions

The primary objective of this review is to provide a comprehensive analysis of the current state-of-the-art in Digital Twin and AI-enabled agriculture. This paper systematically examines the foundational architecture, advanced modeling techniques, applications across core agricultural domains, quantification of performance benefits, and the identification of pressing socio-technical challenges and future research directions.

Key contributions include

1. A systematic examination of the architectural hierarchy of agricultural DTs, distinguishing between Digital Models, Digital Shadows and the fully integrated Digital Twin.
2. A synthesis of advanced modeling approaches, emphasizing the increasing importance of hybrid models that fuse mechanistic principles with data-driven AI for interpretability and enhanced predictive accuracy.
3. A quantitative assessment of DT applications across nutrient, water and stress management, documenting empirical gains in resource efficiency and yield forecasting.
4. A critical analysis of technical, operational, and ethical challenges, including data sovereignty, algorithmic transparency and the ecological footprint paradox of digital infrastructure.

2. Foundational Architecture and Modeling of Agricultural Digital Twins (DTs)

2.1. Historical Evolution: From Physical Mock-ups to Cyber-Physical Systems (CPS)

The foundational principles of the Digital Twin concept originated not in agriculture, but in aerospace engineering. NASA pioneered the concept in the 1960s with the development of a "living model" used during the Apollo missions. This model utilized a combination of physical simulations and digital elements to conduct in-depth failure analysis based on the ongoing assimilation of data (Peladarinos, 2023) [35]. This historical precedent established the core mechanism of continuous data assimilation and analytical replication.

Modern agricultural DTs are integrated Cyber-Physical Systems (CPS) that seamlessly merge the physical farm environment—the soil, crops, livestock, and machinery—with advanced computational models. The operational backbone of DT implementation relies on a sophisticated technological stack, including the Internet of Things (IoT) for data acquisition, along with cloud and edge computing for processing and storage (Zhang, 2025) [51]. Beyond the core data processing, Extended Reality (XR) technologies, such as Virtual, Augmented, and Mixed Reality, are integral to the user interface. These technologies combine the physical and virtual worlds, allowing farmers to immerse themselves in entirely artificial environments or overlay digital information onto the real field, significantly enhancing perception and remote interaction with the DT (Peladarinos, 2023) [35]. Furthermore, DTs increase operational efficiency by allowing farmers to manage operations remotely and simulate the effects of any intervention based on real-life data, without physically compromising real equipment or field resources.

2.2. The DT Hierarchy: Digital Model, Digital Shadow, and Bidirectional DT Integration

A crucial element in evaluating the functional maturity and application capability of any agricultural DT implementation understands its level of data integration (Table 1). The field recognizes a systematic progression through three distinct levels of digital representation, determined by the achievable extent of data flow between the physical asset and its virtual counterpart (Peladarinos, 2023) [35].

Table 1: Levels of Digital Twin Integration and Functionality in Agriculture

Concept	Data Flow	Integration Level	Primary Function
Digital Model (DM)	Manual/Static	None (Initial Modeling)	Simulation, Mathematical Modeling, Detailed Planning
Digital Shadow (DS)	Automated (One-way: Physical → Digital)	Monitoring and Visualization	Real-time Status Assessment, Decision Evaluation (e.g., condition monitoring)
Digital Twin (DT)	Bidirectional (Fully Integrated)	Remote Control and Automation	Predictive Modeling, Optimized Adaptive Control, Prescriptive Action

A Digital Model (DM) is a baseline representation of an existing or planned physical object (Tagarakis, 2024) [45]. It relies on manual data integration and lacks automated data exchange. DMs are useful for initial planning and mathematical modeling, but a change in the physical farm status does not automatically update the digital representation (Tagarakis, 2024) [45].

Building upon this, a Digital Shadow (DS) involves an automated, one-way data flow from the physical object (the field or crop) to the digital object (Peladarinos, 2023) [35]. This integration level is superior as changes in the physical state impact the digital object, allowing for real-time sensor data integration and current condition monitoring for decision evaluation in areas like irrigation or fertilization (Tagarakis, 2024) [45]. However, modifications made within the DS do not directly affect the physical field, limiting the system to an advisory capacity.

The highest level is the Digital Twin (DT), which requires bidirectional, fully integrated data flows. This full integration is the threshold that transitions the system from passive observer to active controller. In a DT, the digital object may function as a controlling instance for the physical asset, meaning changes in one directly affect the state of the other (Tagarakis, 2024) [45]. For instance, in open-field agriculture, this bidirectional exchange allows farmers to receive real-time data and simultaneously exercise remote control, such as adjusting a fertigation unit or controlling pump flow, enhancing decision-making and adaptability in the dynamic agricultural realm (Melesse, 2025) [32]. The successful implementation and standardization of this bidirectional integration layer is therefore the operational goal of high-fidelity DT development, transforming the system into a true autonomous Cyber-Physical System.

2.3. The Data Layer: Integration of Sensing and High-Throughput Phenotyping (HTP)

The fidelity of the DT is directly proportional to the quality and volume of data inputs. The data layer is a complex composite, amalgamating inputs from diverse, disparate sources including environmental sensor networks, IoT devices, meteorological predictions, and high-resolution imaging data from Unmanned Aerial Vehicles (UAVs) and satellites (Melesse, 2025) [32].

A critical enabling technology is High-Throughput Phenotyping (HTP). DTs leverage HTP tools, often integrated with AI, to rapidly assess the appearance and physiological performance of a genotype under distinct environmental conditions (Zhang, 2025; Pandey, 2024) [33, 51]. This comprehensive data collection is essential for predicting crop growth patterns and managing resilience to stress. Crop-specific metrics, such as growth stages, leaf area index, and biomass estimates, are continuously fed into the system via IoT sensors, establishing a dynamic and current model of crop development.

Despite these advancements, significant research gaps remain in the sensing technology. Current crop wearable sensors typically convert phenotype and environmental information into limited electrical signals, which may not capture critical physiological information (Jana, 2024) [17]. For example, a key indicator like nitrogen content often cannot be monitored accurately. To overcome this, future research must prioritize developing new sensing technologies, such as utilizing spectral information and sound signals, to expand the application range of flexible sensors, particularly for crops with complex physical structures like fruit trees with thick bark (Jana, 2024) [17].

3. Synergies with Artificial Intelligence and Decision Systems

3.1. Data-Driven Insights: Applications of Machine Learning (ML) and Deep Learning (DL)

Artificial intelligence algorithms are vital for translating the immense datasets generated by DTs into meaningful insights and management decisions (Bautista, 2025) [4]. By analyzing complex patterns within the spatiotemporal agricultural data, AI models provide precise forecasts and optimize complex procedures.

The integration of ML, DL, and IoT has led to demonstrably enhanced profitability and improved resource management in various applications (Bautista, 2025) [4]. In optimizing farm procedures, AI-driven DT systems have surpassed traditional methods, attaining classification accuracy of 98.65% in Precision Farming (PF)-oriented classification procedures when applied to benchmark datasets (Bautista, 2025) [4]. Specific implementations include utilizing advanced algorithms, such as YOLO V7, integrated into DT models for real-time analysis to accurately predict crop yields and optimize planting strategies. Furthermore, in complex livestock DT applications, lightweight Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) models, often embedded in edge devices, have achieved over 90% accuracy in recognizing specific feeding and rumination behaviors, illustrating the efficacy of AI across diverse agricultural domains (Rao, 2025) [39].

3.2. Hybrid Modeling: Fusing Mechanistic Crop Models with AI for Enhanced Fidelity

One of the most promising technological developments in DT construction is the move toward hybrid modeling. This approach addresses the inherent limitations of using purely data-driven or purely mechanistic models alone. Mechanistic (physics-based) models are rooted in mathematical and computational frameworks that provide detailed, interpretable insight into underlying biological mechanisms (e.g., crop growth or physiological systems) but often struggle with scalability and efficient parameter estimation due to computational expense (Shahhosseini, 2021) [41]. Conversely, purely data-driven AI models offer superior predictive power and efficiency in handling large datasets but typically function as opaque 'black boxes,' lacking interpretability (Behmann, 2015) [5].

Hybrid models integrate mechanistic crop growth models with ML techniques to capture both the underlying biological processes and the complex, non-linear patterns present in observational data (Feng, 2022) [10]. This methodology significantly improves prediction accuracy. For instance, the use of hybrid ML models has demonstrated superior performance in handling intricate spatiotemporal nonlinearities, returning high correlation coefficients (e.g., an $R2$ value of 0.9847) compared to individual modeling techniques.

Empirical studies confirm the performance benefits: when predicting dryland wheat yields, the Agricultural Production Systems sIMulator (APSIM) combined with machine learning (APSIM-ML) weighted ensemble model significantly outperformed standalone ML and APSIM models (Li, 2024) [26]. This hybrid optimization resulted in average improvements in the Root Mean Square Error (RMSE) and Relative Root Mean Square Error (RRMSE) (Shahhosseini, 2021) [41].

Beyond technical performance, the imperative for hybrid modeling is inextricably linked to the socio-ethical requirements of the DT system. Since opaque 'black box' algorithms dictate practices, they can foster distrust among end-users (Cartolano, 2024) [7]. By grounding the predictions in verifiable mechanistic models, the system incorporates inherent biological and physical interpretability (Shams, 2024) [42]. This integration supports Explainable AI (XAI) principles by making the prediction mechanisms transparent, which is vital for building farmer confidence and ensuring that optimized recommendations are understood and trusted.

3.3. Enabling Prescriptive Action: Deep Reinforcement Learning (DRL) for Autonomous Control

The goal of a high-fidelity DT is not merely prediction, but autonomous, optimized control. Deep Reinforcement Learning (DRL) provides the methodology to achieve this prescriptive capability, particularly when overcoming the complexity of explicitly modeling the physical laws of the real system (Goldenits, 2024) [12]. DRL is being used to develop intelligent DTs for automated decision machines, relying on a data-driven approach coupled with supervised model training to learn specific phenomena (Goldenits, 2024) [12].

The system predicts the learned phenomenon in real-time and, in the event of deviation from the optimum, utilizes a DRL algorithm to calculate and execute the necessary optimization strategy (Goldenits, 2024; Zarbakhsh, 2025) [12, 49]. This is crucial for maintaining optimal production quality and optimizing system-wide efficiency, such as in intelligent drying systems (Khdoudi, 2024) [20]. The synergy between DRL and DTs is highly promising for future research, offering solutions to tackle complex agricultural challenges and optimize farming processes autonomously, paving the way for more efficient and sustainable farming methodologies (Lee, 2022) [24].

4. Frontier I: Precision Nutrient Management and Soil Health

4.1. Real-Time Soil Composition Analysis and Fertility Mapping

Maintaining soil health is fundamental to agricultural productivity and ecosystem sustainability. DTs, leveraging AI, are enhancing soil monitoring by integrating multi-source data including remote sensing, physical soil sensors, and historical data to generate precise forecasts of soil characteristics, health indicators, and potential crop yields. This data-driven approach offers a reliable and scalable framework for continuous soil health assessment, moving beyond traditional periodic sampling toward proactive management (Kashyap, 2021; Puniya, 2025) [18, 36]. Future prospects for these systems focus on increasing agrarian sustainability by overcoming the technical and operational problems arising from data heterogeneity and integration difficulties (Figure 1).

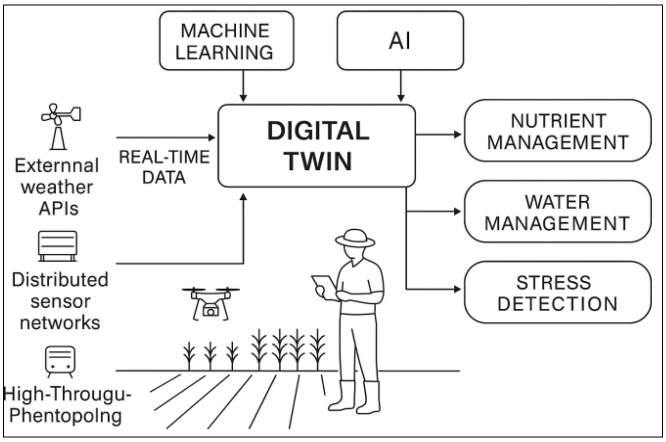

Fig 1: Framework of a Digital Twin-Enabled Precision Agriculture System

4.2. DTs for Fertilizer Recommendation Systems and Input Optimization

Digital Twins play a direct role in optimizing resource inputs by integrating real-time data streams. DTs continuously assimilate data from soil sensors, crop health metrics, and detailed weather forecasts to determine the precise timing and optimal quantity of fertilizer application (Escribà-Gelonch, 2024) [9]. This targeted approach significantly minimizes waste and improves overall crop yields.

The successful implementation of DT models for nutrient management yields substantial, quantifiable sustainability benefits. Studies indicate that optimized fertilization practices based on DT predictions can result in a significant reduction in fertilizer usage, with reported savings ranging from 30% to 40% (Gund, 2025) [14]. This reduction is critical not only for operational cost savings but also for mitigating environmental pollution from nutrient runoff.

4.3. Yield Forecasting Accuracy and Impact on Logistic Planning

Accurate yield forecasting is essential for logistical planning, contract management, and financial risk mitigation (Lee, 2025) [25]. DT models provide a transformation in this domain by analyzing a comprehensive suite of factors including soil health, localized weather conditions, and precise crop growth metrics to forecast yields with high accuracy, reaching up to 91.69% with advanced models like DTEDs.

This high predictive capability, often achieved through hybrid modeling techniques, allows farmers to make profoundly smarter decisions regarding resource allocation and market strategies. To ensure maximum accuracy, the DT must be designed to monitor the dynamic flow of water and nitrogen between the soil and crops, as these processes exert the greatest influence on final yield prediction. The high demand for this specific physiological and environmental data reinforces the strategic necessity of developing advanced, non-destructive sensing techniques to monitor internal nitrogen content, which is currently a limitation of many wearable sensors (Jana, 2024) [17].

5. Frontier II: Dynamic Water Management and Water Use Efficiency (WUE)

5.1. Modeling Crop Water Requirements and Evapotranspiration Estimation

Water management represents one of the most mature applications of agricultural DTs, largely due to the relatively robust physical models available for fluid dynamics and soil-water transport (Katimbo, 2023) [19]. DT technology provides a real-time virtualization of the agricultural environment, continuously integrating live data from distributed sensor networks and external weather APIs to accurately model crop water requirements.

The integration of advanced Machine Learning and Deep Learning algorithms, such as CatBoost and stacked regression, has further refined the estimation of key hydrological indicators. These models enhance the accuracy of estimating Evapotranspiration (ET) and the Crop Water Stress Index (CWSI) by effectively integrating real-time weather and soil moisture data (Lv, 2025) [28].

5.2. Optimal Irrigation Scheduling and Prediction Algorithms

Digital Twins allow farmers to move from reactive irrigation to proactive management through sophisticated scenario testing. Farmers can simulate various environmental conditions, such as droughts or localized stress events, and test different intervention strategies without risking real-world crop losses (Alves, 2023) [1].

These predictive systems yield significant and quantifiable efficiency improvements. Precision irrigation systems enabled by DTs have boosted crop yields by 5% to 15% while achieving substantial water use reductions of 25% to 40%. In terms of scheduling reliability, data-driven systems utilizing ML algorithms, such as Linear Discriminant Analysis, have demonstrated high predictive efficiency, reaching up to 91.25% in determining optimal irrigation timing (Lakhiar, 2024) [23]. The robustness and immediate ecological and economic benefits observed in water management establish this domain as a benchmark for successful high-fidelity DT implementation in agriculture.

5.3. Implementation of Bidirectional Control for Automated Irrigation Infrastructure

The success of water management DTs is closely tied to their achievement of the bidirectional data flow necessary for closed-loop control. Irrigation control software powered by Digital Twins transitions the system from merely analytical support to fully operational automation. This functionality provides predictive intelligence and automation, making irrigation a proactive process (Alves, 2023) [1].

The DT platform for irrigation districts utilizes its predictive modeling capability to forecast water demand and develop optimal distribution schemes (Manjunath, 2023) [31]. Critically, this bidirectional exchange allows for prescriptive automation: the system supports the precise, remote adjustment of physical assets, including controlling pumps, valves, and the opening of gates at various levels (Melesse, 2025; Manjunath, 2023) [31, 32]. This remote operational capacity reduces the need for constant on-site supervision and ensures balanced, efficient allocation of water resources, fully leveraging the dynamic relationship between the virtual replica and the physical infrastructure (Manjunath, 2023) [31].

6. Frontier III: Proactive Crop Stress and Resilience Management

6.1. Early Detection of Biotic Stresses (Pests and Diseases) through HTP and Computer Vision

Biotic and abiotic stresses result in serious food production losses globally, necessitating the deployment of efficient detection and mitigation measures (Zhang *et al.*, 2025; Li *et al.*, 2024) [26, 51]. DTs are central to this effort by enabling the early identification of stress signatures through High-Throughput Phenotyping (HTP) integrated with advanced AI.

High-throughput systems utilize robotic aerial vehicles (UAVs) and high-resolution imagery to generate accurate datasets, which are then processed using Machine Learning (ML) and Deep Learning (DL) (Zhang *et al.*, 2025) [51]. Advanced ML models perform pattern recognition, feature extraction, and predictive modeling to facilitate proactive anomaly detection and stress forecasting, thereby mitigating significant yield losses. The methodologies for biotic stress detection include a range of sophisticated techniques, such as nucleic acid-based and immunological methods, as well as imaging-based techniques, spectroscopic methods, and machine-vision-based methods for pest monitoring (Li *et al.*, 2024) [26]. The development of new sensing technologies remains essential to overcome the limitations of current crop monitoring systems (Jana, 2024; Singh, 2016) [17, 44].

6.2. Predictive Modeling of Abiotic Stresses (Drought, Salinity, Temperature)

Abiotic stresses, including high salinity, extreme temperatures, and drought, influence nearly every stage of the crop life cycle, impacting gene expression, cellular metabolism, and developmental processes (Goldenits, 2024) [12]. While crops possess a degree of resistance, this fails when stress intensity escalates, leading to abnormal growth or mortality (Goldenits, 2024) [12].

Digital Twins, often integrated with cutting-edge techniques such as automated machine learning (AutoML) and quantum machine learning, are emerging as critical solutions for modeling these stresses, advancing precision agriculture, and enhancing crop resilience against changing climatic conditions (Basit, 2025) [3]. Operational tools, such as the CropSmart Digital Twin (CSDT), leverage remote sensing and advanced computer modeling to take the guesswork out of crop management, providing easily accessible services for farmers managing major commodity crops like wheat, corn, and rice (Li, 2024) [26].

6.3. Simulation of Intervention Strategies and Performance Quantification

A primary benefit of the DT environment is the ability to conduct safe, risk-free experimentation. Farmers are able to simulate the consequences of various interventions such as adjusting water regimes or applying protective agents based on real-life data before deploying them in the physical field. This capability extends to complex robotic deployments. Virtual prototyping within the DT allows engineers to test a robot's efficiency, mobility, and functionality in a simulated environment, identifying and rectifying potential issues (e.g., mechanical failure or environmental challenges) without incurring real-world costs or damages (Verdouw, 2021) [46].

The widespread deployment of DTs has provided empirical evidence of their capacity to generate substantial performance gains, particularly in resource optimization and prediction accuracy (Alves, 2019) [2]. These quantitative improvements define the utility and commercial viability of DT adoption depicted from table 2.

Table 2: Quantified Performance Metrics of Digital Twin and AI Integration in Agriculture

Application Area	Metric	Observed Range / Accuracy	Mechanism	Citation
Crop Yield Prediction	Prediction Accuracy	Up to 91.69%	Hybrid Modeling (Mechanistic + ML, e.g., DTEDs)	Zhang, 2025
Crop Yield Prediction	General Prediction Accuracy	85%-90%	Comprehensive DT system performance	Zhang, 2025 [51]
Nutrient Management	Fertilizer Use Reduction	30%-40%	Optimized fertilization practices	Zhang, 2025 [51]
Water Management	Water Use Reduction / WUE	25%-40%	Optimized scheduling, Automated control	Zhang, 2025 [51]
Water Management	Irrigation Prediction Efficiency	Up to 91.25%	Data-driven ML Algorithms (Linear Discriminant Analysis)	Tagarakis, 2024 [45]
Livestock Management (Dairy)	Feed Conversion Efficiency Enhancement	15%-20%	Hybrid edge-cloud CNN-LSTM models for behavior recognition	Shams, 2024 [42]

7. Impediments to Widespread Adoption and Socio-Ethical Governance

7.1. Technical Challenges: Data Standardization, Interoperability, and Rural Infrastructure Deficiencies

Despite the transformative potential, the widespread adoption of agricultural DTs faces significant technical and operational barriers. The core technical hurdle is the massive volume of diverse and high-quality data required for DTs, posing continuous challenges in data management, accuracy, and security (Zhang, 2025) [51].

Integration with existing systems is frequently hampered by pervasive interoperability issues, exacerbated by proprietary data formats and legacy infrastructure. The lack of a standardized approach for developing 3D crop models further impedes effective DT implementation and cross-platform utility. Operationally, the open, non-discrete nature of agricultural and forestry environments makes applying a uniform definition for a full-level DT difficult in practice (Wang, 2024) [47]. Furthermore, successful DT deployment is constrained by the persistent lack of essential infrastructure in rural environments, particularly limited computing power, data storage challenges, and poor device connectivity due which prevents the necessary real-time data flow for optimal functioning. Finally, widespread adoption requires a significant transformation in workforce skills across the entire agricultural value chain, necessitating substantial training and a dynamic environment for effective implementation (Purcell, 2023) [37]. The major constraints to DT implementation across technical, operational, and socio-ethical domains are summarized in Table 3.

Table 3: Major Constraints to Digital Twin Implementation in Agriculture

Category	Specific Challenge	Impact on Digital Twin Adoption
Technical	Data Fragmentation and Interoperability	Hinders holistic integration across proprietary systems; prevents standardization of 3D crop models (Rao, 2025) [39]
Technical	Rural Connectivity and Computing Power	Limits real-time data flow and edge processing crucial for autonomous control (Puniya, 2025) [36]
Operational	Workforce Skill Transformation	Demands significant changes across the agricultural value chain for effective implementation
Socio-Ethical	Data Ownership and Privacy	Violations cause farmer reluctance, preventing the collection of necessary high-volume datasets (Singh, 2016) [44]
Socio-Ethical	Algorithmic Transparency	Opaque 'black box' predictions erode farmer trust and hinder operational validation (Behmann, 2015) [5]
Socio-Ethical	Ecological Footprint Paradox	Computational demand adds to hidden environmental pressures (e.g., data center energy use) (Behmann, 2015) [5]

7.2. Ethical Frameworks: Addressing Data Sovereignty, Privacy, and Security

The rapid digitalization of farming introduces profound socio-ethical challenges, primarily centered on data governance. The current architecture of agricultural data systems often results in the fragmentation and privatization of data streams. Data generated from farm operations such as soil metrics and machinery performance flow into disparate, proprietary cloud platforms, which creates an immediate dependency and severely limits the farmer’s ability to integrate and analyze their own information holistically. This centralized, corporate control of farmer data fundamentally threatens data sovereignty (Behmann, 2015) [5].

Farmers are justifiably worried about the privacy implications, specifically the unauthorized access, collection, and sharing of their proprietary data with third parties by Agricultural Technology Providers (ATPs) (Cartolano, 2024) [7]. Ambiguous agreements and a lack of clear legal frameworks exacerbate this situation. The violation of privacy can lead to a demonstrable reluctance among farmers to adopt new technologies, creating a substantial drag on technological advancement (Zhang, 2025) [51].

7.3. Societal Concerns: Algorithmic Transparency, Bias, and Ecological Impact

A critical governance requirement for ensuring DT success is establishing algorithmic transparency. Opaque ‘black box’ algorithms that dictate farming practices without explanation erode trust and create challenges for accountability (Behmann, 2015) [5]. Ethical considerations require careful management of data ownership, privacy, and algorithmic bias to ensure reliable system outcomes (Shi, 2025) [43].

It is important to recognize that the socio-ethical challenges regarding data governance actively create technical constraints. If farmers restrict access or provide incomplete datasets due to fears of unauthorized sharing, developers are prevented from acquiring the "massive amounts of diverse and high-quality data" necessary to construct and train high-fidelity, generalized DT models (Tagarakis, 2024) [45]. Therefore, resolving fundamental issues such as data ownership and transparency is not merely an ethical mandate but a primary technical bottleneck that must be addressed to advance DT capabilities (Tagarakis, 2024) [45].

Finally, there is an ecological paradox inherent in digital sustainability. While AI promises to reduce agriculture's environmental footprint through precision (e.g., reduced fertilizer use), the supporting digital infrastructure warrants careful ethical consideration. The lifecycle assessment of AI systems, including hardware manufacturing and the high energy consumption of massive data center operations, represents a hidden ecological cost that challenges the 'green' promises of the technology. This "gray reality" of energy consumption must be integrated into the ethical discourse surrounding DT deployment (Behmann, 2015) [5].

8. Future Research Directions and Emerging Paradigms

8.1. Generative AI and Foundation Models in Agricultural Digital Twins

The integration of Generative AI (GenAI) and large-scale Foundation Models (FMs) represents a pivotal advancement for next-generation agricultural Digital Twin (DT) systems. Generative AI encompassing deep generative architectures such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), diffusion models, and multimodal transformers—provides the computational capacity to synthesize high-fidelity data, automate model parameterization, and simulate complex environmental or biological dynamics with exceptional realism. These capabilities are particularly transformative in agriculture, where DT performance is often constrained by data scarcity, environmental heterogeneity, and incomplete sensor observations (Krupitzer, 2024) [22].

Recent breakthroughs demonstrate that GenAI can generate biologically meaningful synthetic datasets that augment sensor inputs, bridge observational gaps, and enhance model generalizability across diverse climatic and edaphic conditions (Kingma & Welling, 2013; Ho *et al.*, 2020) [16, 21]. Within DT frameworks, such synthetic augmentations accelerate the calibration of mechanistic-AI hybrid models, enabling more robust simulations of nutrient transport, plant-soil interactions, and dynamic stress responses. GenAI’s capacity to infer latent structures further supports rapid scenario-based simulations, simultaneously reducing computational load and improving predictive fidelity.

Foundation Models trained on multimodal agricultural data including remote sensing imagery, soil spectra, environmental time-series, and phenotyping datasets offer a unified, scalable representation of complex biophysical processes. These models provide cross-crop and cross-region adaptability, addressing a long-standing bottleneck in agricultural DT deployment. Emerging evidence shows that multimodal FMs enable zero-shot and few-shot predictions for novel environments or emerging stressors, thereby supporting real-time agronomic decision-making under uncertainty (Bommasani *et al.*, 2021; Ramesh *et al.*, 2022) [6, 38].

In practical deployment, the convergence of DTs and GenAI enables automated simulation-driven optimization for nutrient scheduling, irrigation control, pest-disease risk assessment, and climate resilience analysis. Diffusion-based generative models have shown exceptional performance in reconstructing missing environmental variables and forecasting spatiotemporal stress signatures, providing critical inputs for DT-enabled prescriptive control systems (Croitoru *et al.*, 2023) [8]. This synergy positions GenAI as a catalyst for advancing DTs from predictive analytics toward fully autonomous agronomic control systems capable of self-optimizing operational decisions.

Realizing this potential requires rigorous biological validation, physiologically constrained generative pipelines, and standardized integration frameworks to ensure synthetic outputs remain agronomically credible. Further research must also address computational sustainability, as high-capacity GenAI and FM architectures entail significant energy demands. Nonetheless, the convergence of Digital Twins, Generative AI, and Foundation Models signifies a transformative trajectory toward scalable, interpretable, and climate-resilient precision agriculture (Krupitzer, 2024) [22].

8.2. Integrating Explainable AI (XAI) for Farmer Trust and Biological Insight

The necessity for algorithmic transparency mandates the integration of Explainable AI (XAI) principles into DT development. To ensure the rigorous verification and biological plausibility of AI-generated recommendations, particularly in sensitive areas like nutritional or irrigation advice, XAI must be coupled with biologically grounded mechanistic models (Razak, 2024) [40].

This Hybrid XAI approach is essential because mechanistic models provide a framework for understanding *why* an AI prediction was made, thereby overcoming the interpretability deficit of purely data-driven methods (Alves, 2023) [1]. The future demands the development of models that are predictive, efficient, and inherently interpretable, ensuring that farmers not only receive optimized prescriptions but also gain mechanistic insight into the underlying biological or physical processes driving those recommendations (Alves, 2023) [1].

8.3. Advancements in Edge Computing and Federated Learning

To handle the immense data flow and the requirement for real-time responsiveness, hybrid edge-cloud architectures are emerging as the optimal computational topology for DT systems. Edge computing allows for lightweight models, such as CNN-LSTM networks, to be embedded directly into field devices (e.g., sensors or microcontrollers) for millisecond-level data synchronization and immediate anomaly detection, while the cloud handles complex, resource-intensive mechanistic simulations and multi-objective optimization algorithms (Glaroudis, 2020) [11].

Furthermore, the need to scale advanced AI systems, particularly Foundation Models, across diverse farming operations while respecting data privacy requires innovative architectural solutions. Federated learning protocols allow models to be trained on decentralized data held by individual farmers or organizations without centralizing the raw, proprietary information (Zhang, 2023) [50]. This distributed training mechanism is crucial for scaling DTs across large regions while technologically adhering to the necessary ethical frameworks of data sovereignty and privacy, effectively turning the ethical bottleneck into a solvable technical challenge. The cutting edge of research will focus on standardizing the interfaces that efficiently couple privacy-preserving federated learning with robust, biologically constrained physics-based models (Mamba, 2023) [30].

9. Conclusion

Digital Twins are emerging as a cornerstone technology for next-generation agriculture, offering a unified framework that couples mechanistic crop and soil models with advanced AI, real-time sensing and autonomous control. Across nutrient management, irrigation optimization and crop stress resilience, DT systems consistently demonstrate substantial gains in prediction accuracy, input efficiency and operational precision, validating their potential as a transformative engine for sustainable intensification. The integration of hybrid modeling linking physics-based simulations with ML, DL and DRL further enhances system fidelity, enabling prescriptive decision-making and closed-loop control. Complementary advances in High-Throughput Phenotyping, edge computing, generative AI and multimodal Foundation Models strengthen real-time responsiveness and cross-environment scalability, while XAI frameworks provide essential interpretability for farmer trust and biological validation.

Despite these advancements, widespread DT adoption remains constrained by data fragmentation, interoperability gaps, rural infrastructure deficiencies, and unresolved challenges in data sovereignty, privacy, and algorithmic transparency. Addressing these barriers together with establishing biologically grounded generative pipelines, standardized sensing frameworks, and energy-efficient computational architectures will be pivotal for scaling DTs across diverse production systems. Looking forward, the convergence of DTs with GenAI- enhanced simulations, federated learning, and adaptive edge-cloud architectures positions agricultural DTs to evolve into autonomous, self-learning systems capable of generalizing across crops, climates, and management regimes. Such advances outline a scientifically robust and practically viable pathway toward resilient, efficient, and climate-adaptive digital agriculture.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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