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Creating virtual AI models of digital twins on farms to simulate and predict performance under different climatic conditions.

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Abstract

The agricultural sector is undergoing a transformative phase driven by the increasing integration of advanced digital technologies. Digital twin technology has emerged as a cutting-edge innovation capable of revolutionizing precision farming practices by enabling real-time farm simulation and dynamic decision support. Smart farming has introduced agricultural systems that are increasingly autonomous and highly interconnected. A digital twin is a virtual representation of a physical farm system that continuously updates through data streams derived from sensors, machinery, and environmental inputs. This technology facilitates advanced modeling, predictive analytics, and real-time optimization of agricultural operations. Digital twin modeling is essential for accurately representing the physical entity, and it provides functional services and meets the requirements of modern farms. This study provides a detailed analysis of the key aspects of ADTs, providing deeper insights into the potential application areas in agriculture, and discusses major implementation challenges. This study explores applications of ADT in controlled environment agriculture, soil and irrigation management, crop monitoring and cultivation support, post-harvest activities, livestock monitoring and management, and agricultural machinery. It provides intelligent, adaptive, and dynamic facility management and farming decision-making suggestions. The contribution of the project is to develop an ecosystem of digital twins that collectively capture the behavior of a greenhouse facility.

Key Words: agriculture, cyber-physical systems, Federated learning, Digital twin, Smart agriculture

1. Introduction:

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). 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). 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). 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). 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)

Creating virtual AI models of digital twins *on farms allows producers to create a real-time, digital replica of their fields, crops, and machinery to simulate performance under varying environmental, climate, and management scenarios. By feeding data from IoT sensors, satellites, and drones into AI algorithms, these systems can predict outcomes such as yield, crop health, and resource needs, allowing for proactive, data-driven decisions that increase resilience to climate change.*

Key Aspects of Agricultural Digital Twins

Real-time Simulation & Prediction: *Digital twins use historical data, real-time data, and predictive modeling (AI/ML) to forecast future crop performance. These models can simulate crop growth, drought impacts, or flood* *conditions, helping farmers select the best management practices.*

Climate-Resilient Farming: *AI models analyze data to identify crop varieties that can withstand extreme heat or drought. They enable simulating the impact of climate scenarios (e.g., changing precipitation patterns) on pasture growth or crop yields, reducing risks for farmers.*

Resource Optimization: *Digital twins optimize inputs such as water and fertilizers. For example, in India, digital twins have helped reduce forecasting errors by up to 30%, assisting in better water management during erratic monsoons. They can reduce water usage by 25–40% and fertilizer use by 30–40%.*

Precision Breeding and Seeding: *Bayer uses digital twins to create a virtual replica of millions of potential farming acres, allowing them to test and select the best genetic combinations (seeds) for specific field environments before planting.*

Technological Components & Implementation

Data Sources: *IoT sensors (soil moisture, temperature), drones (high-resolution imaging), satellite imagery, and weather stations.*

AI and Machine Learning: *These algorithms process vast data points to identify patterns, such as early indicators of disease or pest infestations, often with an accuracy rate exceeding 90% in yield predictions.*

Modeling Approaches:

Physics-based: Models crop behavior using physical processes like photosynthesis.

Data-driven: Uses machine learning to detect anomalies and optimize resources.

Hybrid: Combines physics and AI for improved accuracy.

Benefits and Future Outlook

Increased Productivity & Sustainability: *Enhanced decision-making boosts yields and reduces the environmental footprint, supporting sustainability goals.*

Risk Mitigation: *Virtual testing enables assessing the consequences of actions, such as delaying irrigation, without real-world consequences.*

Overcoming Challenges: *Despite high initial costs and the need for high-quality data, the technology is advancing to include more user-friendly platforms suitable for smallholder farmers.*

Use Cases

Greenhouse Automation: *In the Netherlands, digital twins are used to simulate light recipes and control the microclimate to optimize tomato growth.*

Livestock Management: *Digital twins can track animal health and behavior, predicting poor health to enable prompt intervention.*

Field Management: *In the U.S., pilot projects are using digital twins to simulate whole cropping seasons before seeds are planted*

2. Review Objectives, Structure, and Key Contributions

The fundamental concept of a DT, which involves a connected virtual representation of a physical object or system, appears to be relatively straightforward. However, its application and implementation can differ significantly across various domains and industries.

Figure 1: Digital twin models create virtual duplicates of real techniques or workout routines. They are handy tools for understanding, optimizing, and predicting behavior in complex systems. Digital twins connect real-time data to more sophisticated simulation tools to help firms make decisions and innovate efficiently. ***Source: https://www.xcubelabs.com/blog/generative-ai-for-digital-twin-models-simulating-real-world-environments/***

Although it is quite clear that in addition to their core purpose of modelling real-world systems, DTs are designed to empower individuals to make informed business decisions with tangible impacts on the physical realm, a clear definition of the DT concept may be helpful to distinguish it from related concepts such as simulation, modelling, and data analytics. By defining its scope, characteristics, and capabilities, researchers and practitioners can better identify the specific features and requirements that make a system a true DT.

2.1. Definition of Digital Twins—What Does the Term "Digital Twins" Stand For?

The definition of DTs emerged in the early 2000s by Michael Grieves, while evolving to a widely acceptable DT concept model where they act as a bridge connecting physical entities in the real world with their virtual complements in a digital environment, closing the gap between the two. They establish vital connections between data and information to seamlessly integrate these products' virtual and real aspects. The convergence of virtual and physical entities in a virtual space and the real world lays the foundation for creating a fundamental DT model. By fostering dynamic interplay between these tangible and virtual elements, the DT is a powerful representation of the combined physical-virtual system.

The outlines that DTs act as digital replicas of physical systems and are organized by establishing data connections. This transformation enables physical systems to exist virtually while ensuring a strong synchronization between their physical and digital counterparts. As a result, smooth interactions and data exchange occur between the two domains.

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.

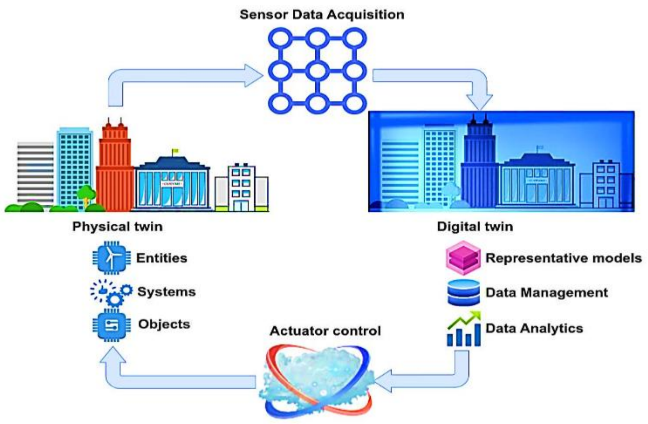

Figure 2: The generic representation of a DT scheme's dynamic integration of physical and digital domains. Source: *Peladarinos, Nikolaos, et al., 2023.23(16), 7128; https://doi.org/10.3390/s23167128*

2.2. 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.

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

Foundational architecture and modeling of Agricultural Digital Twins (ADTs) involve the integration of physical assets, virtual representations, and bidirectional data, information, and service flows. These systems, currently in an emerging phase, enable continuous, real-time synchronization between in-field operations (soil, crops, machinery, livestock) and their virtual counterparts for simulation, prediction, and optimization

3.1. 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). 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). 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). 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.

4. 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 is understanding its level of data integration. 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). A Digital Model (DM) is a baseline representation of an existing or planned physical object (Tagarakis, 2024). 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). 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). 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). 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).

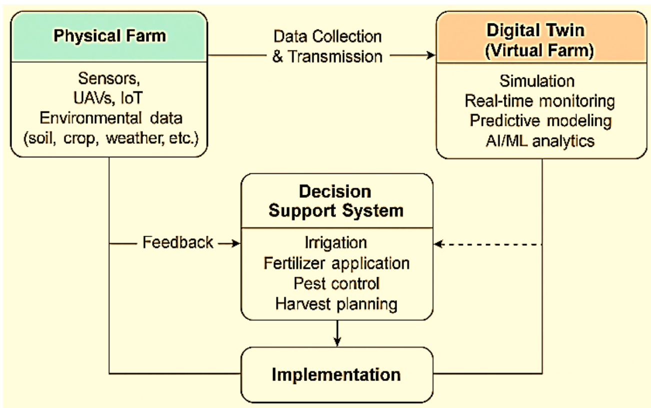

Figure 3: Block Diagram of DTs Architecture in Smart Farming. Source: Agri. Engineering 2025, 7(5), 137; https://doi.org/10.3390/agriengineering7050137

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).

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). 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). 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). 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).

5. Synergies with Artificial Intelligence and Decision Systems

5.1. 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). 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). 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). 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).

5.2. 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). 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). 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).

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 R^2 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 the machine learning (APSIM-ML) weighted ensemble model significantly outperformed standalone ML and APSIM models (Li, 2024). This hybrid optimization resulted in average improvements in the Root Mean Square Error (RMSE) and Relative Root Mean Square Error (RRMSE) (Shah Hosseini, 2021). 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). By grounding the predictions in verifiable mechanistic models, the system incorporates inherent biological and physical interpretability (Shams, 2024). This integration supports Explainable AI (XAI) principles by

Figure 4: Views of AI digital twins in farming (the opportunities and challenges for AI digital twins in farming). ***Source: https://www.devdiscourse.com/article/technology/3835567-opportunities-and-challenges-for-ai-digital-twins-in-farming***

making the prediction mechanisms transparent, which is vital for building farmer confidence and ensuring that optimized recommendations are understood and trusted.

6. How Generative AI Enhances Digital Twin Models

The integration of generative AI in digital twin models is already a significant step toward the simulation, prediction, and optimization of real-world environments, and the combination of generative AI into them is groundbreaking. Let us peek at how differently advanced technologies cooperate to transform an industry.

6.1. So, how does generative AI enhance digital twins?

6.1.1. Data, Data Everywhere: Generative AI can create synthetic data, especially when real-world data is limited or unavailable. This helps us train our models more effectively and build more accurate simulations.

6.1.2. Supercharging Model Fidelity: AI algorithms can optimize the parameters of our digital twin models to make them more accurate and realistic, leading to better simulations and predictions.

6.1.3. Real-time Magic: We can update our digital twins in real time, mirroring the most egregious changes in the real world.

6.2. Let's take a look at some real-world examples:

Manufacturing: To optimize production and downtime, simulating scenarios, including various procedures and downtime.

Healthcare: Digital twin model simulations with AI allow testing of new treatments, predictive control, and personalized patient treatment. Generative AI in digital twins has contributed to a 25% reduction in patient wait times by optimizing ICU operations and workflows. Urban Planning: Detailed digital twins of cities can help us analyze traffic flow, energy consumption, and other urban challenges. Digital twins for smart cities, enhanced by generative AI, have enabled 20% improvements in energy efficiency and better traffic management through detailed scenario simulations.

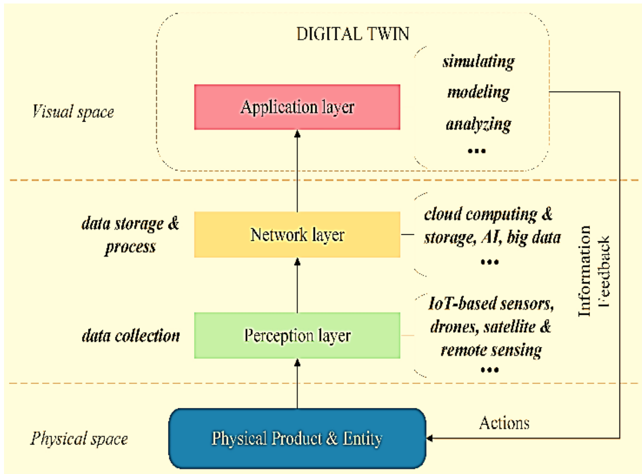

Figure 5. The architecture of digital twins and the functions of each layer. Source: Agriculture 2025, *15*(9), 903; https://doi.org/10.3390/agriculture15090903

6.3. 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). 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). This is crucial for maintaining optimal production quality and optimizing system-wide efficiency, such as in intelligent drying systems (Khdoudi, 2024). 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).

7. Precision Nutrient Management and Soil Health

7.1. 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).

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

7.2. 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). 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). This reduction is critical not only for operational cost savings but also for mitigating environmental pollution from nutrient runoff.

7.3. Yield Forecasting Accuracy and Impact on Logistic Planning Accurate yield forecasting is essential for logistical planning, contract management, and financial risk mitigation (Lee, 2025). 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).

8. Dynamic Water Management and Water Use Efficiency (WUE)

8.1. 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). 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).

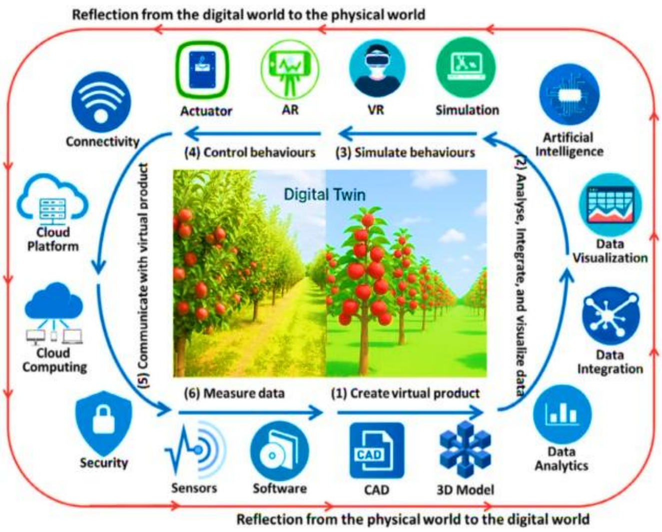

Figure 6: Opportunities and challenges in the application of digital twins for orchard management. Source: https://doi.org/10.1016/j.compag.2025.111104

8.2. 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). 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). 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.

8.3. 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). 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). 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).

9. Proactive Crop Stress and Resilience Management

9.1. 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). 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). 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). The development of new sensing technologies remains essential to overcome the limitations of current crop monitoring systems (Jana, 2024; Singh, 2016).

9.2. 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). While crops possess a degree of resistance, this fails when stress intensity escalates, leading to abnormal growth or mortality (Goldenits, 2024). 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). Operational tools, such as the Crop Smart 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).

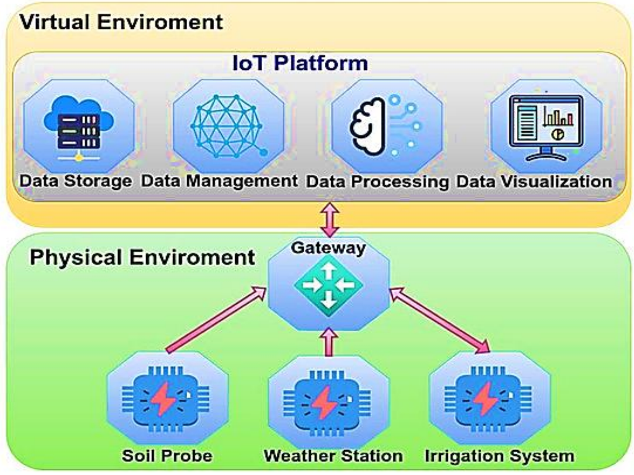

Figure 7: Connection entities over an IoT platform overview. (Through the IoT, users can seamlessly provide contextual data to their DT while receiving feedback that can be used to enhance their interaction with the environment, both locally and remotely. Various communication technologies within IoT are required to transmit data and status information from sensors in the physical entity to the data entity, enabling seamless connectivity and communication between connected devices). Source: Peladarinos, Nikolaos et al., 2023, *23*(16), 7128; https://doi.org/10.3390/s23167128

9.3. 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). 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).

10. Impediments to Widespread Adoption and Socio-Ethical Governance

10.1. 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). 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 International Journal of Research in Agronomy https://www.agronomyjournals.com ~ 175 ~ 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). 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).

The rapid digitalization of farming introduces profound socioethical 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). 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). 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).

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). Ethical considerations require careful management of data ownership, privacy, and algorithmic bias to ensure reliable system outcomes (Shi, 2025). 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). 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). 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).

10.2. Digital twins bring virtual modeling to precision agriculture

In agriculture, these systems integrate sensor networks, environmental monitoring tools, simulation models, and AI-driven analytics to mirror the conditions of crops, soil, equipment, and climate in near real time.

The concept relies heavily on modern sensing technologies. Soil probes measure moisture levels, nutrient concentrations, and temperature changes. Weather stations track environmental variables such as humidity, solar radiation, and wind patterns. Drones capture aerial imagery that can reveal crop stress, disease outbreaks, or growth variability across fields. These diverse datasets are then transmitted through digital communication networks and processed by cloud or edge computing systems that update the digital model of the farm.

AI plays a key role in interpreting these data streams. Machine learning algorithms can analyze imagery captured by drones to identify disease symptoms or estimate crop biomass. Predictive models can forecast how soil moisture levels will evolve over time or how environmental conditions may affect plant growth. When integrated into a digital twin framework, these algorithms enable the system to simulate different management strategies and predict their potential outcomes.

For farmers, the practical benefits could be significant. A digital twin could simulate irrigation scenarios before water is applied, helping farmers avoid overwatering or drought stress. Nutrient models could predict fertilizer requirements more accurately, reducing both costs and environmental impacts. Digital twins of machinery could monitor equipment performance and predict maintenance needs before failures occur.

Although these capabilities remain largely experimental, the research reviewed in the study suggests that even partial implementations of digital twins can improve agricultural decision-making. Systems that combine sensor data with predictive models can already provide early warnings about plant stress, nutrient deficiencies, or mechanical problems, allowing farmers to intervene earlier and manage resources more efficiently.

11. AI drives smarter agricultural digital twins.

AI and machine learning technologies are vital to the development of digital twins in agriculture. While early digital twin concepts relied mainly on simulation models, modern implementations increasingly integrate AI algorithms that enable systems to learn from data and make adaptive predictions.

In crop monitoring systems, machine learning models analyze images captured by drones or ground-based cameras to detect patterns that indicate crop health or disease. These algorithms can identify stress signals in plants, estimate yield potential, and map variations across fields. When linked to a digital twin environment, such insights can inform decisions about irrigation, fertilization, and pest control.

Similarly, machine learning models are being applied to soil monitoring and nutrient management. Sensor data collected from soil probes can feed into predictive algorithms that estimate nutrient availability, soil moisture dynamics, and microbial activity. These predictions allow digital twins to simulate how crops may respond to different environmental conditions or management strategies.

Another area where AI is gaining traction is the monitoring and maintenance of agricultural machinery. Digital twins of tractors, cultivators, and other equipment can use real-time telemetry data to track operational performance and detect anomalies. Predictive maintenance algorithms can identify early signs of mechanical wear or malfunction, enabling farmers to repair equipment before breakdowns disrupt field operations.

The study also notes that AI can help address some of the limitations inherent in agricultural data collection. Agricultural environments often produce noisy or incomplete datasets due to sensor failures, environmental interference, or gaps in monitoring coverage. Machine learning models can compensate for missing data or adjust predictions based on historical patterns, improving the reliability of digital twin simulations.

However, the integration of AI into agricultural digital twins remains uneven across the research landscape. Many digital twin implementations still rely primarily on simulation models with limited machine learning capabilities. In other cases, AI tools are used as supplementary components rather than central elements of the digital twin architecture.

12. Barriers prevent digital twins from reaching full potential.

The study highlights several challenges that currently limit their widespread adoption in agriculture. One of the most significant barriers is data integration. Agricultural datasets often come from heterogeneous sources, including drones, sensors, weather stations, satellite imagery, and simulation models. These data streams may vary in resolution, frequency, and format, making it difficult to combine them into a unified digital twin model.

Sensor networks themselves also present practical challenges. Many agricultural sensors are deployed in harsh outdoor environments where dust, humidity, vibration, and temperature fluctuations can affect reliability. Communication networks may suffer from unstable wireless connections, missing data packets, or limited coverage in remote rural areas. Battery limitations further constrain the ability of sensors to transmit continuous real-time data.

Another limitation concerns computational complexity. Detailed models of plant growth, soil processes, or environmental dynamics can require substantial computing resources. Running such simulations in real time may not be feasible without significant computational infrastructure, particularly for large farms or regional agricultural systems.

The review also finds that most digital twin experiments are conducted in controlled environments or small-scale field trials. Long-term evaluations of digital twin systems operating across full farming seasons are rare. This lack of real-world testing makes it difficult to assess how well these systems perform under the complex and unpredictable conditions of commercial agriculture.

Economic considerations represent another obstacle. Implementing digital twin systems requires investments in sensors, communication networks, computing infrastructure, and data management platforms. For many farmers, particularly those operating small or medium-sized farms, these costs may outweigh the perceived benefits of adopting such technologies.

The study raises concerns about data governance and ethical implications. Digital twin systems collect detailed information about farm operations, environmental conditions, and management practices. Questions about who owns this data, how it is stored, and who can access it remain largely unresolved in the current research landscape.

Privacy issues may also arise when aerial imagery or sensor networks capture data beyond the boundaries of individual farms. The authors suggest that future digital twin implementations will need to address these governance challenges through clearer policies on data ownership, access rights, and security.

13. Toward scalable digital twins for sustainable agriculture

Future research directions identified in the study include the development of multi-scale digital twin systems capable of connecting farm-level models with regional environmental and climate data. Such systems could help farmers anticipate long-term risks related to climate variability, water availability, and soil health.

Another priority is the creation of standardized architectures and interoperable data pipelines that allow different agricultural technologies to communicate more effectively. Currently, many digital twin projects operate within isolated technical frameworks, making integration across platforms difficult.

The study also calls for stronger collaboration between engineers, agronomists, and farmers to ensure that digital twin technologies address real-world agricultural needs rather than remaining purely experimental research tools. Incorporating user feedback and practical farming knowledge into system design could help bridge the gap between technological innovation and field deployment.

14. Future Research Directions and Emerging Paradigms

14.1. 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). 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) . 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. Gen AI'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). 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). 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).

14.2. 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). 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). 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).

14.3. 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). 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. 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).

15. High-Level Architecture for Proposed Digital Twin Use Cases in Agriculture

The diagram illustrates the proposed architecture of a DT system for smart agriculture that integrates cloud, fog, and edge computing layers and multi-agent systems. Farmers or users can access a DT system through a farm management GUI (Graphical User Interface). The overall architecture consists of three layers: Cloud, Fog, and Edge.

The Cloud layer plays multiple roles, including accessing external services like growth stage estimators, weather services, routing services, and disease identification tools. It also offers data storage and anonymization services for farm data and supports machine learning and data analysis. Additionally, data collected from satellites that help with growth stage estimation, weather prediction, and disease identification are stored in this layer. This layer is also responsible for handling complex processing tasks that are not time-sensitive and can utilize the vast resources of cloud computing.

15.1. The Fog layer consists of two sub-zones: the Static Fog Zone and the Mobile Fog Zone. In a smart or precision farming setup, an array of sensors and actuators are employed, along with machinery like harvesters, tractors, and innovative devices such as drones and agricultural robots. These devices function as mobile fog nodes, gathering data directly from the fields. Located at the field level, the Static Fog Zone hosts agents, microservices, and digital twins, providing localized data storage and computing capabilities for immediate analysis of farm data.

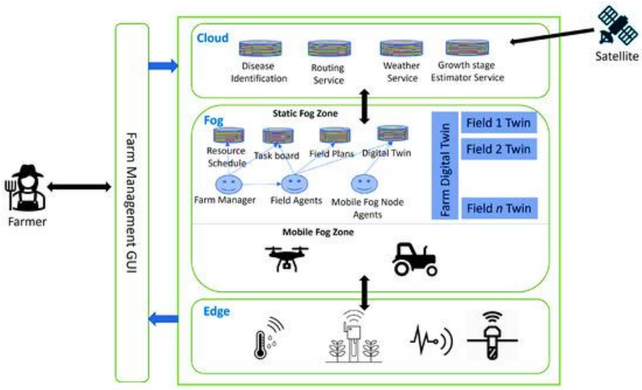

Figure 8: Proposed Architecture for Digital Twins in Smart Agriculture. ***Source:*** **Future Internet** ***2024,*** **16*(3), 100; https://doi.org/10.3390/fi16030100***

The mobile fog nodes serve to extend the reach of the Fog network, ensuring data collection and processing capabilities in parts of the farm that may have intermittent or no internet access. Furthermore, the fog layer incorporates a collection of microservices, which facilitate access to both internal APIs for farm data retrieval and third-party APIs (Application Programming Interfaces) for extended functionality. It also houses various agents, such as the farm manager and field agents, who are tasked with resource scheduling, task management, and the execution of field plans. These components function seamlessly within both the static and mobile zones of the fog layer.

The Edge layer comprises various devices with embedded sensors and actuators utilized in agricultural environments. These devices can include soil moisture sensors located directly in the field or NDVI sensors mounted on farm machinery such as tractors. These Edge devices connect to the static Fog layer to transmit data when internet connectivity is present. In the absence of connectivity, mobile Fog nodes provide data collection services, gathering information from the Edge devices either opportunistically or upon request. This allows for continuous data acquisition and integration into the farm's DT system, ensuring that the farm management has access to the most updated information for decision-making.

Additionally, the overall architecture incorporates MAMS (Multi-agent Micro-services) as illustrated in Figure 8. In this setup, microservices are tasked with ongoing activities like weather monitoring and are engaged in the continuous processing of data. The system's flexibility allows seamless transitions between different data sources, like switching from one weather station to another, by simply re-configuring the appropriate microservice. This adaptability level is a fundamental feature of DT technology and is further enhanced by the integrated multi-agent system. In this interconnected environment, actions in one field can influence outcomes in another. The DT plays a crucial role in fine-tuning these decisions, utilizing data-centric simulations. At the core of this architecture is the utilization of established agricultural guidelines, such as the RB209 recommendations, providing a solid foundation. These guidelines are not just followed; they are dynamically adapted to suit the real-time conditions of the farm, ensuring the advice provided is both reliable and contextually relevant. On the other hand, agents play a crucial role in the DT framework, particularly in decision-making, task allocation, and resource management. These intelligent agents utilize the data gathered by microservices to make not only decisions but also recommendations. A comprehensive knowledge graph is built by a variety of microservices, such as those collecting weather data, nutrient recommendations, and decision-making services. This interconnected data representation enables agents to coordinate system activities effectively. This ensures the maintenance of the most accurate model of the field's state. The agents are focused on developing an efficient plan for the field. Although this plan is not a built-in feature of the DT, it is significantly influenced by the data collected and analysis from the DT. This field plan directly impacts nutrient levels, which in turn affects the growth stages of the crops. Efficient management of the DT, coupled with the use of intelligent agents for decision support, enables us to recommend strategies that maintain optimal field conditions, enhancing both the productivity and efficiency of agricultural practices. The agents can also analyze patterns, predict outcomes, and allocate tasks efficiently across the farming operation. Their capabilities include assessing the best planting strategies, optimizing irrigation schedules, and managing resource allocation to maximize yield and efficiency.

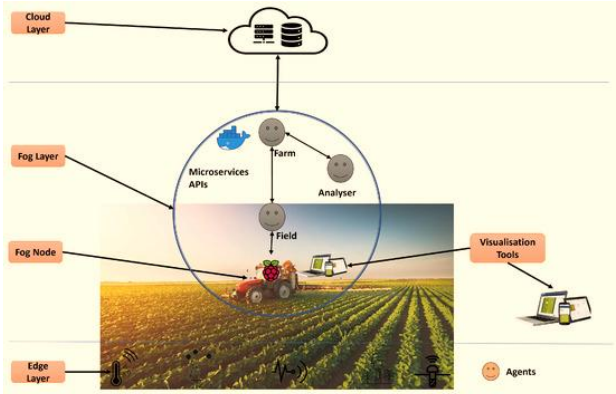

Figure 9: Cloud–Fog–Edge and MAMS Overview. Source: Future Internet 2024, *16(3), 100;* https://doi.org/10.3390/fi16030100

16. Digital Twins of the Earth System via Hybrid Physics-AI Models

The Earth system is a nonlinear, multiscale, Multiphysics dynamical system that includes the atmosphere, ocean, land, cryosphere, and biosphere. Representation of this system requires the resolution of numerous processes at a range of spatiotemporal scales, from micrometers (e.g., cloud microphysics) to thousands of kilometers (e.g., planetary circulation) and seconds to centuries. This breadth necessitates an important modeling design balance: spatiotemporal resolution and physical fidelity versus computational cost and time to solution. Such balance is a central consideration in the development of general circulation models (GCMs) and their more comprehensive forms: Earth system models (ESMs). Collectively, these models comprise mathematical equations that describe the Earth system's physical processes. Scientists use them to simulate weather and climate, though they inevitably carry the inherent limitations and uncertainties of representing the real world.

Building upon these foundations, *digital twins*—virtual replicas of real-world systems that combine models, data, and widely-used decision frameworks from engineering and other applied science disciplines, two are an emerging paradigm in the Earth system domain. For example, Destination Earth is a European Commission initiative that applies digital twin technology to simulate weather and climate. Indeed, if we take the formal definition of a digital twin—"*a set of virtual information constructs that mimics the structure, context and behavior of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle, and informs decisions that realize value*", One we can find three key components that are already part of Earth system modeling workflows, especially in the context of weather and climate simulations. These are as follows:

- A model (*a set of virtual information constructs*)
- Data (from its *physical twin* counterpart)
- *Decisions that realize value*.

The underlying *models* are GCMs and ESMs. They are continuously updated with *data* from their physical twin—i.e., the Earth—that originate from satellite or air- and ground-based observations. The models' outputs inform *decisions that realize value*, from advanced warnings of impending hurricanes to assessments of long-term climate risks that guide policy, adaptation, and mitigation strategies. Time is extremely important here, both in terms of (i) dynamical updates of the digital twin with data and (ii) the timeframe that provides information for *decisions that realize* *value*. A common assumption is that a digital twin should be continuously updated with data from its physical twin. However, “continuously” can have different meanings depending on the context. The key is then to provide information for *decisions that realize value*, which occur at different time scales based on the predictability horizon of the application in question and the cost-loss balance of the envisioned action. Time scales can range from minutes to hours (e.g., nowcasting for aviation and flash flood alerts), days to weeks (e.g., evacuations or electricity grid dispatch), season to season (e.g., crop-sowing windows or reservoir operations), or even years to decades (e.g., infrastructure design, insurance, and climate policy). These horizons determine the frequency at which physical twin data should be updated or ingested. Indeed, the prediction horizon and frequency of data ingestion depend on the specific application; for instance, the data update requirements and prediction horizons of a spacecraft are quite different than those of Earth’s weather and climate applications.

17. Conclusion

Visualization of the digital twin of the greenhouse makes it easy to operate and control the system. It helps to strengthen the agriculture system. Less labor work and timely and accurate prediction result in minimal economic loss. The relevance of the project is reduced farmers difficulty in managing greenhouses without frequent visits. The major relevance of this project is that we can enlarge it from a small scale to a large scale. That means with the help of the software we can monitor a single unit of a greenhouse to large no of greenhouses. That is from a home to an industrial level. It bridge the gap between technology and agriculture. It is easy-to-use interface and it contribute towards the field of Machine learning. In conclusion we can say it drives innovation and performance. Improve the customer and farmers experience. It provides intelligent, adaptive, and dynamic facility management and farming decision-making suggestions.

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 Gen AI-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.

18. Ethics declarations

18. 1. Ethics approval and consent to participate

Not applicable.

18.2. Consent for publication

Not applicable.

18.3. Competing interests

The authors declare that they have no competing interests.

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The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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28. Background: The integration of Artificial Intelligence (AI) in agricultural practices has witnessed substantial advancements, with a focus on enhancing efficiency and sustainability. This research explores the application of AI-powered robotic harvesting systems for legume crops, aiming to revolutionize traditional harvesting methods. By leveraging machine learning algorithms and robotic technology, this study investigates the feasibility and performance of such systems in terms of precision, speed, and resource optimization.

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