

Review

A Comprehensive Review of Digital Twins Technology in Agriculture

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Abstract: Digital Twin (DT) technology has emerged as a transformative tool in various sectors, like agriculture, due to its potential to improve productivity, sustainability, and decision making processes. This paper provides a comprehensive review of the applications, challenges, and future directions of DT technology in agriculture. We explore the key concepts and architecture of DTs, focusing on the layering and classification of DT systems. The review delves into the various applications of DTs, such as crop planting management, pest and disease control, livestock management, optimization of agricultural machinery and resource, and agricultural decision support systems. Furthermore, we highlight the integration of agricultural data acquisition, simulation, and modeling techniques that form the backbone of effective DT implementation. Despite its promising potential, the adoption of DTs in agriculture faces several technical challenges, including data acquisition issues, integration difficulties, and the standardization of 3D crop models. Finally, we discuss future direction of DT technology, emphasizing the importance of overcoming existing barriers for wider application and sustainability.

Keywords: digital twin; smart agriculture; precise agriculture; IoT



Academic Editor: Francesco Marinello

Received: 26 February 2025

Revised: 7 April 2025

Accepted: 12 April 2025

Published: 22 April 2025

Citation: Zhang, R.; Zhu, H.; Chang, Q.; Mao, Q. A Comprehensive Review of Digital Twins Technology in Agriculture. *Agriculture* **2025**, *15*, 903. <https://doi.org/10.3390/agriculture15090903>

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1. Introduction

The agricultural sector has long been at the forefront of adopting technological advances to address the growing global demand for food and the challenge of sustainable production [1,2]. As the world faces significant pressures related to population growth, climate change, and environmental degradation, the need for innovative approaches to agriculture has become more urgent [3,4]. The trend towards digitalization and automation in agriculture has accelerated. In recent years, with the advent of cutting-edge technologies such as the Internet of Things (IoT) [5], Artificial Intelligence (AI) [6–8], and Digital Twin (DT), these technologies commit to revolutionize agriculture by improving efficiency, optimizing resource usage, and reducing environmental impact [9].

DT technology, originally for industrial applications, has been widely applied in various sectors, including manufacturing, healthcare, and urban planning [10]. Its ability to create virtual replicas of physical systems has been an essential tool for real-time monitoring, simulation, and predictive maintenance [11].

According to the prevailing taxonomy in digital twin research [12,13], integration levels have advanced sequentially from digital models (static) through digital shadows

(dynamic) to full digital twins (interactive), with each stage defined by data coupling intensity and control capabilities. As shown in Figure 1. A Digital Model (DM) refers to a static, descriptive representation of a physical system, often used for visualization or structural understanding without automatic data updates from the real world. A Digital Shadow (DS) introduces a unidirectional data flow from the physical asset to the digital replica, enabling real-time monitoring and partial synchronization, but lacking full interactivity or bi-directional feedback. In contrast, a DT entails a dynamic, bidirectional communication loop where real-time data continuously updates the virtual model, and insights or simulations from the model can influence the physical system, enabling advanced prediction, control, and optimization processes. As emphasized by Kritzinger et al. [12], a digital shadow can be viewed as a necessary intermediate step toward a true digital twin, particularly in domains like agriculture where infrastructure constraints often limit full bi-directional integration. In this review, we adopt a pragmatic stance by referring to all stages—whether digital shadow or full digital twin—under the term “DT”.

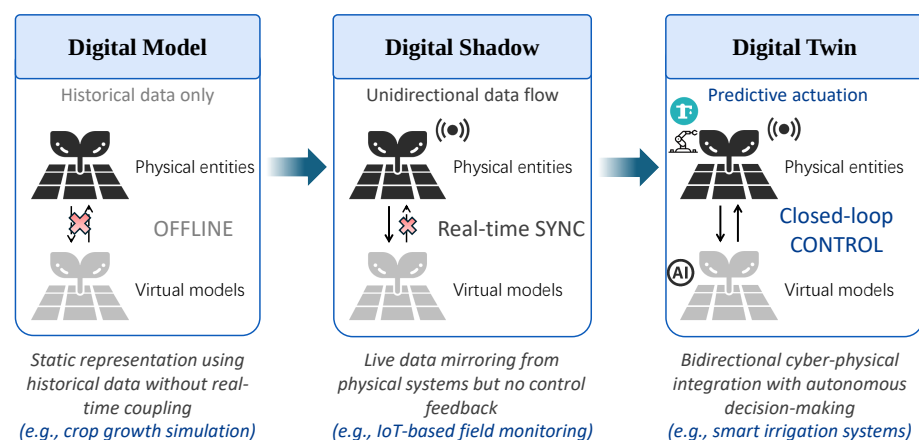


Figure 1. Digital Model vs. Digital Shadow vs. Digital Twin.

In agriculture, DT technology has gained particular application in several key areas. Through the integrated data from sensors [14,15], satellites [16,17], weather systems [18,19], and other digital sources, a DT can mirror and predict the behavior of agricultural systems [20,21], thus enabling more informed decision making [22–24]. For example, it has been applied to crop planting management, where DTs simulate and monitor soil conditions, crop growth, and water use to optimize planting schedules and input applications [25,26]. In agricultural disaster warning and response, DTs have been used to predict pest outbreaks, disease spread, and weather-related disasters [27,28]. Furthermore, livestock management has benefited from the application of DT [29,30], providing farmers with the tools to monitor animal health, breeding cycles and productivity, thus improving animal welfare and farm efficiency [31,32].

There are substantial uncertainties assessing the full potential of DT implementation in precision agriculture [33]. By providing farmers with a holistic view of their agricultural environments, DTs enable them to improve operational efficiency, optimize resource allocation, and reduce environmental impacts [34]. The study by Chaux et al. [35] also highlights how DTs can be applied in controlled environment agriculture to optimize productivity, thus providing valuable information for long-term planning.

Many scholars have recently been making contribution in this field such as Lu et al. [36], who expanded the concept to incorporate IoT, cloud computing, and big data analytics for agriculture. In recent years, DTs have been combined with machine learning (ML) algorithms [37–39] to further improve prediction accuracy and decision making capabilities [40,41].

Researches in the application of DT technology in agriculture have become increasingly important. As the global agricultural landscape continues to evolve, understanding how to optimize agricultural systems using DT will be crucial to ensure crop planting efficiency, reduce environmental impacts, and promote sustainability [42,43]. This review makes the following key contributions to the field of DT in agriculture:

- We systematically examine the current state of digital twin technologies in agriculture, highlighting both the technologies—such as IoT, cloud computing, and edge computing—and their concrete applications of different agricultural issues, including crop management, disaster warning, and resource optimization.
- We identify and categorize the primary technical and operational challenges impeding widespread DT adoption in agriculture. These include difficulties in data collection from heterogeneous sources, lack of standardization, interoperability issues, and high implementation costs, especially in low-resource settings.
- We propose future research directions with a specific emphasis on the integration of DTs and Foundation Models (FMs). Such convergence is anticipated to enhance the intelligence, autonomy, and scalability of agricultural DT systems.

2. Concept and Architecture of DT

2.1. Key Concepts of DT

The concept of DT was firstly introduced by Michael Grieves in the early 2000s [44], focusing on product life cycle management as a virtual representation of a physical product, encompassing relevant information about the product [45]. DT is precisely characterized as a virtual replica of a product, process, or service, incorporating key features of the physical counterpart [46]. Miller et al. [47] expanded this definition, describing DT as an integration of multiple models within a model-based enterprise, where DTs are formed by linking various models and data across different domains. Stark and Damerau [48] offered a broader definition, defining DT as a digital representation of an active, unique product or product-service system, comprising its characteristics, properties, conditions, and behaviors through models, information, and data across one or more life cycle phases. Although minor differences remain in the definition of DT, it can be summarized that DTs function as a bridge between physical entities in the real world and their virtual counterparts in a digital environment, effectively closing the gap between the two [44,49]. The definition and concepts of DT will be discussed from the following perspectives:

Virtual models of physical entities: DTs are virtual counterparts of physical entities, systems, or processes, reflecting their real-world counterparts [46,50,51]. The core idea behind DTs is the continuous exchange of real-time data between the physical and digital worlds, enabling the creation of dynamic, data-driven simulations [12,44]. This interaction allows for the monitoring, analysis, and optimization of the performance, behavior, and life cycle of physical objects, which is crucial for applications like predictive maintenance, performance analysis, and system optimization [52].

Features and applications: A DT is not just a simple model or simulation; it is an intelligent, evolving representation of a physical entity that continuously monitors and controls its life cycle and operations [53,54]. It tracks the performance, condition, and potential faults of the system it represents, making it possible to predict future states such as defects or breakdowns. In addition, DTs can simulate and test new configurations and maintenance procedures, using these insights proactively for operational improvements [52].

Advancements and intelligent interaction: Technological advances have driven the development of DT. Advances in real-time data upload, large-scale data storage, and data fusion technologies enable continuous exchange and updates of descriptive data [11]. Real-

time updates ensure that the DT stays synchronized with its physical counterpart and the surrounding environment.

2.2. Architecture of DT

The physical and virtual space linked through data flow and feedback mechanisms work as the core of DT architecture. The physical space comprises the actual system or entity being monitored, such as machines, vehicles, or agricultural fields [55]. The virtual space, on the other hand, consists of digital models, simulations, and analytics tools that represent the physical entity's behavior, status, and performance [56]. The key challenge in DT architecture is ensuring accurate and real-time synchronization between the physical and virtual counterparts [57]. It is shown in Figure 2 that, this synchronization is enabled through data sensors and devices that collect real-time data from the physical space and transfer it to the virtual environment for processing, analysis, and decision making [58].

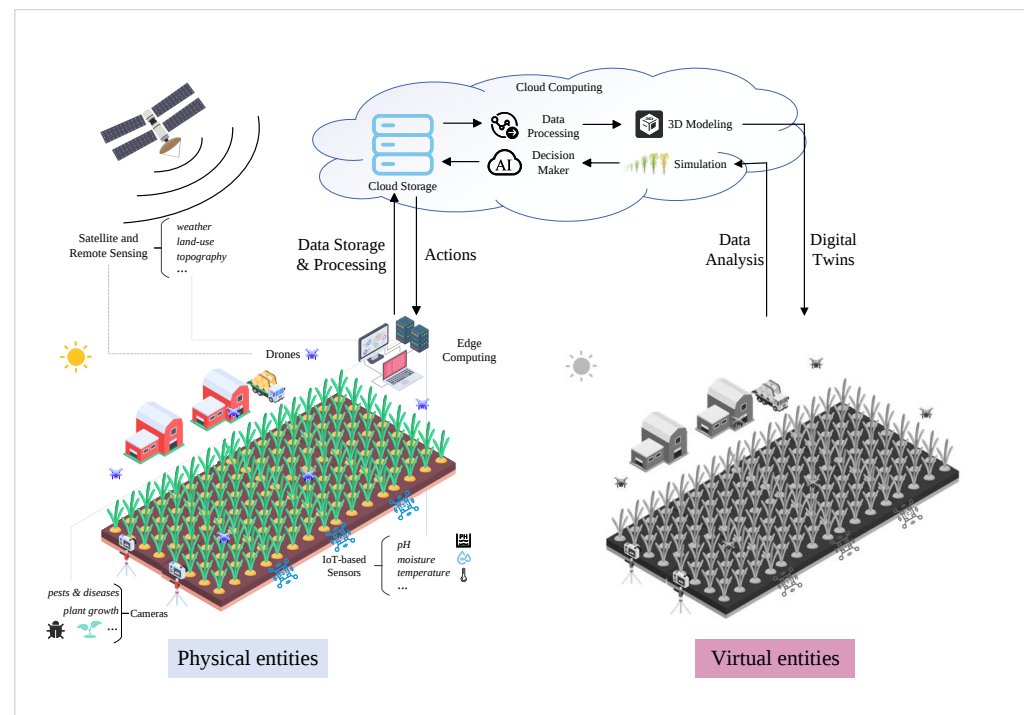


Figure 2. Data acquisition and transmission process.

In Figure 3, the architecture is typically structured in three layers: the perception layer, the network layer, and the application layer. Each layer plays a distinct role in ensuring the accurate representation and functioning of the DT system [59].

Perception layer: The perception layer involves the physical sensors and devices that collect data from the physical environment. This layer is responsible for gathering data on parameters such as temperature, pressure, humidity, location, or speed. The sensors are often distributed across the physical entity, continuously monitoring its state and providing a comprehensive picture of the system's conditions. The data is then transmitted to the next layer through the network infrastructure [60].

Network layer: The network layer acts as a bridge between the perception layer and the application layer. It involves the communication protocols, cloud systems, and data storage mechanisms that enable the transmission of large amounts of real-time data [61,62]. The network layer ensures the smooth flow of data from the physical entity to the virtual space and vice versa. It provides the infrastructure for data transmission, storage, and cloud processing, enabling the system to function in real time [63].

Application layer: At the top of the architecture lies the application layer, which includes the analytics and decision support systems (DSS) that process the incoming data from the physical space. This layer is responsible for simulating, modeling, and analyzing the data to optimize the performance of the physical system [64]. In many applications, the virtual model is continuously refined through feedback from the physical system, allowing for continuous learning and improvement [65]. The application layer also includes user interfaces, dashboards, and reporting tools that provide stakeholders with insights into the performance of the physical system and facilitate decision making [66].

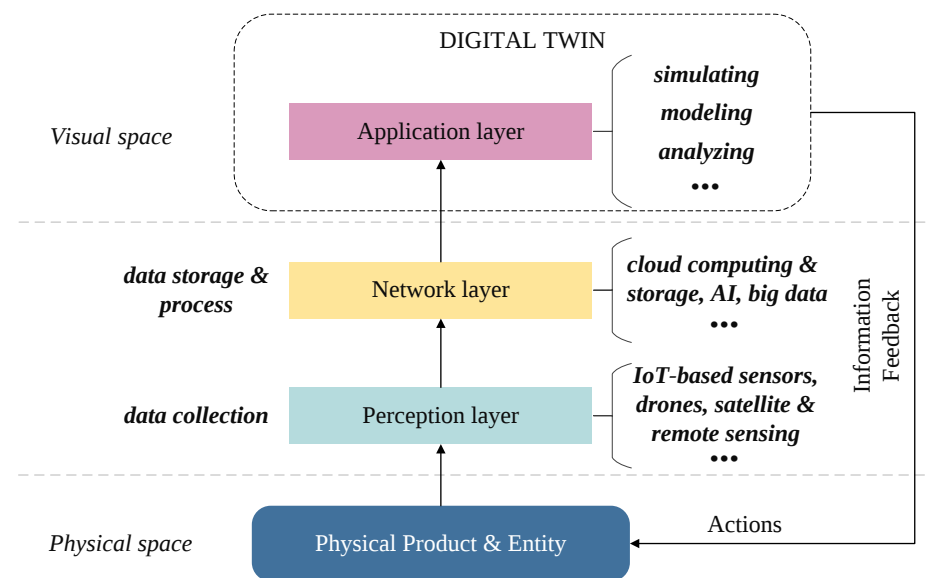


Figure 3. The architecture of Digital Twins and functions of each layer.

The architecture of DT has changed due to advancements in key areas such as computing, communication, and sensing technologies [67]. The specific architecture chosen often depends on the intended goals of the system. For example, Schleich et al. [46] proposed a comprehensive architecture aimed at connecting physical and virtual twins, focusing on aspects such as scalability, interoperability, expandability, and fidelity. In contrast, Alam and El Saddik [68] presented a DT framework tailored to cloud-based cyber-physical systems.

DT architectures can be classified based on their objectives or the scope of monitoring [68]. For example:

Individual DT: Represent single physical objects or systems, typically used for simple or standalone entities such as machinery, equipment, or products. They provide detailed virtual models, facilitating monitoring, analysis, and simulation.

System-level DT: Represent broader systems or processes composed of multiple interconnected components or subsystems. These models offer a comprehensive view of system interactions and dependencies, supporting optimization of product performance, usage tracking, and maintenance practices.

Biomass DT: Model individual or groups of living organisms in virtual environments, commonly applied in sectors such as production, education, or healthcare.

3. Current Research and Key Technologies in Agricultural DT

This section aims to describe the evolution of agricultural DT from theoretical constructs to tangible applications, emphasizing the pivotal shifts and significant breakthroughs in research endeavors within recent timescales. It delves into the key technologies underlying this domain, explaining their crucial roles in fostering the development of

agricultural DT. In addition, it also provides an overview of the applications and emerging research trends within the intersection of agriculture and DT.

3.1. Development of Agricultural DT

As shown in Figure 4, the concept of DT emerged in the early 2000s, initially applied to manufacturing and engineering to digitally replicate physical systems for monitoring, prediction, and optimization. Over the years, the concept has evolved and expanded into other domains like agriculture, where its potential for improving precision agriculture and sustainability is recognized [69].

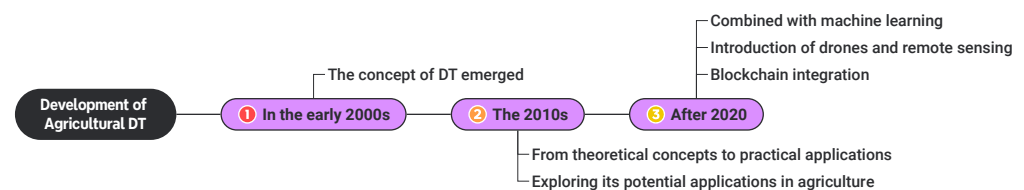


Figure 4. Development of agricultural DT.

The 2010s can be marked the early exploration of DT technology in agriculture. During this decade, DT gradually changed from theoretical concepts to practical applications in the agricultural domain. This period saw a combination of foundational research, early trials of DT frameworks, and incremental improvements in data acquisition and modeling techniques. In the early 2010s, DT technology was primarily limited to manufacturing and aerospace industries. However, researchers began exploring its further applications in agriculture, recognizing the need for integrating digital simulations to optimize resource use and improve yield prediction. Initial efforts focused on conceptual frameworks that emphasized the role of IoT devices for real-time monitoring of soil, crop health, and environmental conditions [70]. For example, early studies proposed using digital model to replicate field conditions digitally, allowing researchers to simulate different crop growth scenarios [71]. However, practical implementation was hindered by limited sensor availability and low computational power.

After 2020, with the advancement of IoT devices, the acquisition of high-resolution data has become crucial for DT development. Precision agriculture gained momentum during this period, leveraging IoT for site-specific crop management. Due to the rise of AI and big data technologies, the use of ML for tasks such as crop production prediction, pest and disease detection has shown promising results [72]. Researchers began developing DT frameworks that combined environmental data (e.g., weather, soil moisture) with predictive models to guide planting and irrigation decisions [10]. Drones and remote sensing technologies were also introduced as key data acquisition tools. These technologies enhanced DT accuracy by providing detailed aerial imagery of fields, which was used to identify crop stress and monitor large-scale agricultural operations [73,74]. Nasirahmadi and Hensel proposed a next-generation digitalization paradigm for agriculture, integrating DT with ML for autonomous decision making. This research highlighted the transformative potential of DT for optimizing irrigation, predicting crop diseases, and reducing resource wastage [75]. In livestock farming, DT can be utilized to monitor animal health and behavior, improving productivity and reducing costs [32]. Blockchain integration [76,77] has also emerged as a key innovation, with studies highlighting its role in ensuring data transparency and security within DT frameworks [78,79].

3.2. Key Technologies in Agricultural DT

There are many technologies involved in an agricultural DT, and this section explores the key technologies that underpin the development and implementation of an agricultural DT. These technologies include advanced agricultural data acquisition methods, which help collect comprehensive and accurate information needed for decision making. In addition, we explore agricultural data storage solutions to address the challenges of managing massive amounts of data efficiently and securely. Finally, the importance of 3D modeling and simulation in creating virtual representations of agricultural systems will be presented.

3.2.1. Agricultural Data Acquisition

Agricultural data acquisition lays the foundation for DT systems in agriculture. Accurate and timely data from the field are critical to building digital representations of physical agriculture systems, enabling real-time monitoring, predictive analytics, and decision making. The integration of advanced sensing technologies, remote sensing, and IoT networks has revolutionized agricultural data acquisition, making it more precise, automated, and scalable [80,81].

(1) IoT-based sensor: IoT-based sensor networks are widely employed in modern agriculture to monitor soil properties, crop health, and environmental conditions. For example, Dhanaraju et al. [82] implemented IoT sensors to gather real-time data on soil moisture, temperature, and pH levels in a smart agriculture setup. These sensors were connected via wireless networks, allowing seamless data transfer to cloud systems for analysis.

(2) Drones, satellite and remote sensing technologies: Drones and satellite imaging have emerged as indispensable tools for agricultural data acquisition [16,83]. Remote sensing technologies provide high-resolution images of fields, capturing detailed information on crop health, soil conditions, and water usage [84]. Peladarinos et al. [10] highlighted the use of UAVs equipped with multispectral cameras to collect crop imagery, which was subsequently used to monitor plant vigor and detect early signs of stress [85,86]. Satellite-based systems, such as the Sentinel series [87] from the European Space Agency, complement UAV data by offering large-scale insights into weather patterns, drought conditions, and land-use changes [88,89]. Combining satellite and drone data significantly enhances the accuracy and scalability of DT in agriculture.

(3) Embedded systems and advanced sensors: Modern agricultural machinery, such as tractors and harvesters, is equipped with embedded systems to collect operational data. Bloch et al. [90] utilized ISOBUS data from sowing machines to automatically initialize crop simulation models in a DT system. This integration ensured that data on seed placement and soil conditions were captured accurately for use in field management simulations. Integration of advanced sensors, such as LiDAR and hyperspectral cameras, has expanded the scope of agricultural data acquisition. Moghadam et al. [91] demonstrated the use of LiDAR sensors to capture 3D representations of crop canopies, enabling detailed analysis of growth patterns and biomass estimation.

(4) Edge computing: Edge computing [92] is increasingly integrated with IoT sensors to enable real-time data processing at the source, reducing the need for data transmission and thus improving efficiency [93]. Fuentealba et al. [94] explored the application of edge computing in 5G-enabled agriculture, allowing on-field devices to preprocess data before transmission to centralized systems. This approach consequently, reduced latency and enhanced the responsiveness of DT systems.

3.2.2. Agricultural Data Storage

Agricultural data storage is a critical component of agricultural DT, facilitating the organization and accessibility of vast amounts of data from various sources such as sensors,

drones, and satellite imagery. Data storage solutions in agriculture must address the challenges related to the scale, complexity, and heterogeneity of data generated in the sector. These challenges have led to the development of sophisticated storage technologies that are capable of handling large datasets while ensuring high accessibility and security.

In agricultural DT, data storage is essential for handling various types of data, including spatial, temporal, environmental, and operational data. Spatial data, such as satellite imagery and drone maps, often comes in the form of raster or vector data, while temporal data might involve time-series data from sensors that measure soil moisture, temperature, and crop growth stages. Operational data could include information on agricultural equipment, irrigation systems [95,96], and inputs such as fertilizers or pesticides. As DTs require real-time or near-real-time data, data storage systems must ensure low latency and rapid retrieval. Traditional relational databases are often insufficient for this purpose, as they struggle with the volume, velocity, and variety of agricultural data.

(1) Cloud computing and edge computing: Cloud computing has emerged as a dominant solution for agricultural data storage. It provides scalable and flexible storage capacity, which is critical given the rapid growth of sensor data and other agricultural datasets [97]. For example, cloud-based platforms allow farmers and researchers to store and analyze data remotely, ensuring they can access information from anywhere at any time. One significant example is the integration of cloud storage with the IoT in agriculture. A study by cloud computing for storing IoT-based agricultural data, providing farmers with enhanced decision making capabilities. These systems can store large quantities of data and use advanced ML algorithms to process and derive actionable insights, such as predicting crop yields or identifying optimal irrigation schedules [94]. Furthermore cloud storage solutions often incorporate redundancy and backup protocols to prevent data loss, ensuring continuity even in the event of system failure. Some systems also support hybrid cloud approaches, combining on-premise storage with cloud capabilities to ensure greater security and control over sensitive data. Edge computing is also another emerging technology in agricultural data storage. Unlike traditional cloud-based systems that require transmitting all data to centralized servers for processing, edge computing involves processing data locally on devices such as sensors or drones [98]. This is particularly advantageous in agricultural settings where the internet may be intermittent, and real-time decision making is required.

(2) Big data: With the exponential growth in agricultural data, traditional data storage solutions are increasingly being replaced by more robust architectures like data lakes. Data lakes store large volumes of raw, unstructured data in its native format. This is particularly important in agriculture, where data types can vary significantly. Big data platforms such as Hadoop and Spark [99] have been used to manage agricultural data lakes, enabling the processing of petabytes of data [100]. These platforms support parallel processing and distributed computing, ensuring that large datasets can be processed in a fraction of the time it would take using traditional systems. One significant advantage of using data lakes in agriculture is that they provide the flexibility to store diverse data types, allowing data scientists and farmers to explore correlations between different datasets [100]. For example, by combining weather data with soil moisture and crop growth data, more accurate predictive models can be developed for crop yield forecasting.

(3) Blockchain technology: Data security is a significant concern in agricultural data storage due to the sensitive nature of the information. Blockchain technology has been proposed as a means to enhance the security and traceability of agricultural data. Blockchain offers decentralized storage with immutable records, making it particularly useful for ensuring the integrity of critical data such as crop yields, pesticide use, and harvest information. A recent study by Rehman et al. [101] explores the potential of blockchain for agricultural data management, providing secure and transparent data

sharing among different stakeholders in the agricultural supply chain. Blockchain ensures that once data is recorded, it cannot be tampered with, thereby fostering trust between farmers, researchers, and consumers. Additionally, blockchain can be integrated with smart contracts to automate transactions based on predefined conditions, such as automatic payments when specific crop growth stages are reached. This reduces human intervention and enhances efficiency in the data storage and processing workflow.

3.2.3. 3D Modeling and Simulation

3D modeling and simulation play an essential role in the development of agricultural DT, as they enable the creation of virtual representations of real-world agricultural systems. These models help simulate crop behavior, environmental interactions, and agricultural operations, allowing for more efficient decision making, resource management, and sustainable agricultural practices [102]. Currently, the majority of virtual scenes in DT are constructed using 3D modeling software in conjunction with game engines such as Unity and Unreal to achieve model building and visualization within virtual environments [103].

One of the primary uses of 3D modeling in agriculture is to replicate crop growth under various environmental conditions. The study conducted by Zermas et al. [104] extracted phenotypic characteristics of corn crops using reconstructed 3D models. By combining data from the Structure from Motion technique with image data, they created a detailed 3D point cloud of the corn crop. This 3D model facilitated the extraction of several phenotypic features, including leaf area and stem position, which are crucial for evaluating crop growth. This study not only showcases the potential application of 3D reconstruction technology in agriculture but also offers ideas and methodological references for future related research. By combining advanced sensors, image processing algorithms, and 3D reconstruction methods, it is possible to capture multi-angle and structural information about plants to create highly realistic 3D models. For example, studies have utilized technologies such as LiDAR, stereo vision, and structured light systems to create detailed 3D reconstructions of plants to measure their growth parameters [105–107].

Simulation in agricultural DT plays a pivotal role in enhancing agricultural practices. The integration of 3D models with real-time data allows farmers and researchers to simulate various agricultural processes such as crop growth, irrigation, and pest control. This integration is vital for forecasting the outcomes of different agricultural practices without implementing them physically. The digital simulations can analyze complex agricultural systems, providing valuable insights into optimizing crop yield, water usage, and pest management strategies. Edemetti et al. [108] utilized drone technology to generate a 3D model of the vineyard, facilitating remote inspection of the vineyard's physical condition by farmers. In smart agriculture, 3D technology can also be used for dynamic simulation of plants and interaction with robots [109,110]. Yandun et al. [111] performed visual 3D reconstruction and dynamic simulation of fruit trees, enabling robots to intelligently interact with the tree canopy.

3D modeling and simulation are essential components of Agricultural DT technologies, offering a powerful means of replicating, analyzing, and optimizing agricultural processes. Through 3D modeling, researchers can create highly detailed representations of agricultural systems, including individual crops, entire fields, and environmental factors [112]. These models are then enhanced with simulation tools that can predict the outcomes of various agricultural practices under diverse conditions. Recent advancements in integrating real-time data, and AI with 3D modeling have propelled the development of adaptive and intelligent agricultural systems, paving the way for more efficient and sustainable farming practices.

3.3. Applications of DT in Agriculture

The section delves into various domains where DTs are revolutionizing agricultural practices, including Crop Production Management (CPM), agricultural disease warning, livestock management, agricultural equipment optimization, agricultural resource optimization, and agricultural DDS.

In Table 1, five case studies are presented to analyze the application scenarios, core technologies, key functionality, validated outcomes and limitations.

Table 1. Agricultural Digital Twin Systems: Case Studies and Technical Specifications

Category	Name	Application Scenario	Technologies	Data Sources	Functionality	Outcomes	Limitations	References
Case 1	Vineyard Support System	Disease prediction & monitor environmental conditions	GIS & IoT & Edge Computing	Sensors & Goidanich Model	Real-time data collection and transmission & Node-based risk alerts: >70%	Achieved 96.9% successful data delivery over 30 days	Short-term testing & Communication dependency & Sensor scope	[113]
Case 2	Autonomous Agricultural Vehicles	Develop autonomous agricultural vehicles	Autoware Framework & Control Algorithms & ROS-based TF	UAV Aerial Imagery & Tractor Parameters	Real-time simulation & Path planning & Rviz visualization for trajectory tracking and lateral deviation analysis	Average lateral deviation of 0.023 m in simulation	Validated only on straight-row operations & Computational load	[114]
Case 3	Feeding Behavior of Dairy Cows	Monitoring and analyzing feeding behavior of dairy cows	UWB & IMU & LSTM	Collar Sensors & Video Observation & Positioning Anchors	Real-time tracking of cow positions and motion & Visualization interface for monitoring cow status and generating alerts	LSTM Accuracy: 94.97% & Precision: 99.99%, Recall: 93.86%, F1 Score: 95.21%	Only five cows tested & Deployment challenges	[115]
Case 4	Smart Irrigation and Rice Leaf Disease Prediction System	Smart irrigation and disease prediction	IoT & WSNs & ANN & ResNeXt-50	WSNs & Remote sensing & Cameras	Real-Time monitoring & Automated irrigation & Disease classification	ANN Accuracy = 0.9427 ResNeXt-50 Accuracy = 0.967	Model complexity & Only focused on rice diseases	[116]
Case 5	Digital Twin for Greenhouse and Underground Environments	Real-time monitoring and optimization	Visible Light Communication & LSTM	Sensors & UAV Aerial Imagery	Real-time monitoring & Multi-modal communication	5G demonstrated the lowest latency (18 ms) & Temperature prediction achieved a mean squared error of 0.5405	Small-scale testing & integration of multiple technologies increase deployment costs	[117]

3.3.1. Crop Production Management

CPM, as one of the most promising applications of DT in agriculture, involves creating a virtual model of fields to simulate environmental conditions, crop growth, and various management practices. CPM has been significant advancements with the integration of DT technology in recent years. DT technology allows the creation of a virtual representation of crops, fields, and environmental conditions, enabling more efficient management practices. Several studies have shown how DTs have been applied to predict crop production, with particular focus on precision agriculture, crop growth simulation, and real-time monitoring.

In the field of agricultural production management, the application of DT technology is gradually changing the traditional agricultural model. Using advanced technologies such as AI and IoT, DT can significantly improve the productivity and efficiency of agricultural production [75].

Crop Growth Simulation: One of the most important studies on using DT in CPM was carried out by Skobelev et al. [118], who developed a DT system designed to simulate and monitor field conditions in real-time. This system was able to incorporate various

parameters such as soil moisture, temperature, and weather conditions to predict crop performance and growth patterns.

Predict Crop Yield: The integration of ML with DT further enhances their ability in CPM. Rajeswari et al. [119] explored the use of ML algorithms integrated into DT models to predict crop yields and optimize planting strategies. The research includes continuous collection of data from IoT based sensors and UAVs, input of DT models, and real-time analysis using advanced AI algorithms such as YOLO V7. Using AI, the DT system can predict crop yield and optimize planting.

3.3.2. Agricultural Disaster Warning and Response

The agricultural system is susceptible to diseases and pests. Traditional methods of disaster management in agriculture often rely on basic models and static data, which fail to provide the real-time, dynamic analysis needed for effective disaster prevention and mitigation. However, the advent of DT technology offers promising solutions for enhancing agricultural disaster warning and response. By creating a real-time virtual replica of agricultural environments, DT can monitor environmental information and crop status in real time, detect the types of crop diseases and pests, and provide information to farmers as well as issue early warnings of diseases and pests.

Disease Detection: Angin et al. [27] used convolutional neural network (CNN) and image reduction sampling technology in disease detection of plant leaves. This model combines crop modeling, environmental data and pest dynamics with ML technology for early detection of pests and disease outbreaks.

Predictive Ability: Dai et al. [120] built a pest management system, collected relevant data at the perception layer and transmission layer through RGB cameras, hyperspectral cameras, various sensors and other environmental acquisition equipment, and the IoT architecture in a controlled agricultural environment, and established an AI based DT model for pest prediction, effectively realizing intelligent management of pests and diseases. In the risk assessment experiment for grey mould infection conducted by Zanchin et al. [121], multiple linear regression was utilized to develop a mathematical model relating grape bunches morphological characteristics to resistance against grey mould, with the objective of predicting the resistance of grape bunches to grey mould infection.

Despite the success of these systems, challenges remain in terms of scalability, data integration, and accessibility for smallholder farmers. The cost of implementing DT systems, the complexity of managing large amounts of data, and the need for accurate and real-time data sources can be barriers to widespread adoption. However, with advances in low-cost sensor technologies, cloud computing, and AI-based algorithms, the potential for DT systems to revolutionize pest and disease management in agriculture continues to grow.

3.3.3. Livestock Management

Livestock management has been an integral part of agriculture. DT technology has proven to be a transformative tool in livestock management, providing a virtual model that simulates both the environment and the animal's condition. DT technology in livestock management offers several advantages, including real-time monitoring, predictive analytics, enhanced decision making, and personalized animal care. By simulating a virtual copy of the livestock and its environment, DT systems provide a comprehensive view of animal health, feeding patterns, and environmental interactions.

Real-Time Monitoring of Animal Health: Traditional methods of monitoring livestock often rely on periodic checks and visual inspections, which can result in delayed detection of health issues. DT systems, on the other hand, continuously collect data from sensors embedded in collars, ear tags, or other wearable devices. This data, which includes

information on temperature, movement, feeding behavior, and other vital signs, is fed into the DT model to create a dynamic representation of the animal's health status. Chen et al. [122] developed a pigsty environment monitoring system using DT technology, enhancing monitoring effectiveness through three-dimensional modeling and system design to better safeguard the health and safety of pigs [103].

Optimize Breeding Strategies: DT of livestock can integrate genomic data, health history, and environmental factors to provide a better understanding of the ideal conditions for breeding. By predicting the outcomes of different breeding pairs, DTs help improve genetic diversity, productivity, and disease resistance in livestock populations. Erdélyi et al. [123] applied DT to the pig fattening process in smart animal husbandry, creating a DT model of the pig fattening process. This model is used to simulate average feed consumption, body mass growth of pigs, and to calculate body mass at specific breeding stages.

3.3.4. Optimization of Agricultural Machinery and Equipment

The optimization of agricultural machinery and equipment is a key component of modern agricultural practices aimed at improving productivity, reducing costs, and ensuring sustainability. Traditional approaches to machinery management, which often rely on periodic maintenance and manual adjustments, are increasingly being supplemented—or replaced—by more sophisticated technologies like DT. Using sensors, IoT technologies, and advanced data analytics, DT systems provide real-time insights into machinery performance, enabling precise decision making and predictive maintenance.

Real-Time Monitoring of Machine Performance: Through the integration of sensors and IoT devices, DT systems continuously collect data from machinery, including parameters such as engine temperature, fuel consumption, soil conditions, and wear and tear of parts. This real-time data is used to generate virtual models of the machinery, which are updated in real-time, allowing farmers and equipment operators to track the condition of their machines remotely. Addressing issues such as inaccurate pressure control and response lag in wet clutches of high-power tractor Power-Shift Transmissions (PST), Zhang et al. [124] introduced the concept of DT and proposed a Digital Twin-Driven Time-Varying Proportional-Integral Adaptive control (DT-TVPIA) method. In 2024, Zhang et al. [125] further proposed an adaptive gear-shifting strategy based on DT. Through the synergistic action of two mechanisms: real-time dynamic precise modeling and automatic generation of gear-shifting strategies, the adaptive adjustment of gear-shifting strategies is achieved. This provides a reference for the application of DT technology in optimal control of complex nonlinear systems.

Improve the Accuracy of Agricultural Machinery: DTs also contribute to the broader field of precision agriculture. De Borton et al. [126] proposed a cost-effective algorithm tailored for autonomous cultivators, with template matching at its core. Based on the results of the template matching, the displacement of the cultivator relative to the crop rows is calculated, guiding the cultivator to perform precise operations.

3.3.5. Resource Optimization in Agriculture

The concept of Resource Optimization using DT in agriculture has been a critical element in improving efficiency and sustainability in agriculture operations. DT technologies offer the capability to create virtual replicas of physical agricultural assets, systems, and processes, which can be used to simulate, monitor, and optimize resource usage (e.g., water, fertilizers, energy, and labor) in real-time. This helps optimize resource management, such as water and fertilizer application, thus enhancing sustainability and agricultural productivity [10].

Managing Irrigation Systems: Water management is a critical challenge in agriculture, especially in regions facing water scarcity. DT technology facilitates real-time tracking and management of irrigation systems. For example, sensor networks installed in the field monitor soil moisture levels, temperature, and rainfall data, feeding this information into the DT model [62]. This data is then processed to simulate irrigation needs, which helps farmers optimize water use by avoiding over-irrigation and ensuring crops receive sufficient water.

Management Fertilizer: Fertilizer optimization plays a crucial role in enhancing crop yield while minimizing environmental impact [10]. By integrating real-time data from sensors (such as soil composition and crop health) and external factors (such as weather forecasts), DTs provide actionable insights into the most efficient fertilizer application practices. This optimization reduces the risk of overuse and runoff, leading to improved environmental sustainability.

Optimize Energy Usage: By creating a virtual model of farm operations, DTs help identify energy inefficiencies across the farm's processes, such as irrigation, harvest scheduling, and machinery usage [34]. This allows farmers to adjust their practices to lower energy consumption, saving costs and reducing carbon footprint. DT models can simulate energy demand based on operational data and seasonal requirements, providing insights that contribute to more sustainable energy management on the farm.

3.3.6. Agricultural Decision Support Systems

DT technology has significantly enhanced agricultural DSS, providing real-time, virtual replicas of physical agriculture assets, systems, and environments. By utilizing data-driven insights from real-world agricultural operations, these systems have made achievements on optimizing agricultural processes, improving resource utilization, and supporting better management decisions. DSS powered by DT offers farmers tools to make informed, data-backed decisions based on continuous monitoring, simulations, and predictive models.

Optimize Agricultural Operations: DTs have been identified as a cornerstone in smart agriculture, facilitating the management and optimization of various agricultural operations. These systems replicate the real-world conditions of crops, livestock, soil, and equipment in a virtual space, allowing for improved decision making. According to the research by Verdouw et al. [60], DT used in agriculture environments, such as arable, dairy, and livestock farming, enable better operational management by allowing real-time control and remote monitoring based on the collected data from IoT devices and sensors. This advanced virtual model supports farmers in identifying problems early, simulating different interventions, and understanding their impacts on the farm's productivity.

Crop Decision Management: By simulating various environmental and agronomic factors such as irrigation schedules, fertilization, and pest control, DT-based DSS can guide optimal farming practices. According to Escribà-Gelonch et al. [69], these systems provide real-time insights into crop health and behavior, enhancing precision agriculture practices. Such systems consider multiple variables, including soil health, weather conditions, and plant growth, ultimately supporting more effective pest management and crop disease prediction. In addition Ghandar et al. [127] proposed a DT decision support system for urban agriculture. Taking aquaculture as a case study, they showed how to cope with the pressure of the global food system through DT and ML.

As DTs integrate with advanced technologies like big data, and ML, they provide farmers with deeper insights into how certain interventions impact farm operations. Nasirahmadi and Hensel discuss the importance of integrating DT-based DSS with IoT sensors, which enables continuous monitoring of soil, irrigation, and crop health parameters. Their study underlines the role of DT in optimizing resource allocation and enhancing sustain-

ability efforts in precision agriculture [75]. In conclusion, DTs serve as a powerful tool in agricultural DSS, offering real-time insights, predictive capabilities, and optimization of various agricultural processes. By continuously monitoring and simulating farming conditions, these systems enable farmers to improve decision making, enhance productivity, and address challenges related to sustainability and resource management.

4. Challenges in Agricultural DT

As DT technology gradually has been applied in agriculture, it shows great potential in many aspects. However, the development of agricultural DT still faces numerous challenges. This section explores the main issues and challenges in agricultural DT from five aspects: data acquisition, data integration, model construction, physical-virtual integration, and full life cycle management.

4.1. Data Acquisition Challenges

Data acquisition serves as the fundamental cornerstone of DT technology, a principle that remains equally valid for agricultural DT systems. Currently, agricultural DTs encounter several significant challenges in data acquisition that impede their widespread adoption and development within the agricultural sector. These critical issues are analyzed in detail below.

(1) Environmental Complexity in Data Acquisition: The agricultural data acquisition environment is characterized by significant geographical and climatic variability, presenting substantial challenges for sensor deployment and data acquisition. Diverse topographical features, including mountainous regions, hilly terrains, plains, and wetland ecosystems, exhibit distinct geographical characteristics that need advanced adaptability in data acquisition instrumentation [32,60,71,128]. Each environmental context presents unique data acquisition challenges. Meteorological conditions further exacerbate data acquisition challenges. For example, precipitation events can induce electrical short circuits in sensors [129], thermal extremes can alter sensor component characteristics, wind forces can displace instrumentation, and freezing temperatures can degrade battery performance and electronic component functionality, thereby jeopardizing data accuracy and temporal continuity.

(2) High Costs in Data Acquisition: The implementation of comprehensive data acquisition systems in extensive agricultural settings requires substantial resource investment. Although IoT technologies have facilitated data acquisition processes [130,131], their widespread agricultural implementation faces substantial barriers, including technological costs, device reliability concerns, and network coverage limitations. For example, the deployment of extensive sensor networks for data acquisition involves not only significant capital expenditure for equipment procurement but also ongoing costs for installation, maintenance, and data transmission. These substantial data acquisition costs represent a major barrier to the widespread adoption and implementation of DT technology in agriculture [60].

4.2. Data Integration Barriers

Agricultural data are typically derived from diverse sources, including sensor networks, satellite remote sensing platforms, agricultural management information systems, meteorological stations, and research institution databases [27,129,132–136]. The integration of these heterogeneous data sources within agricultural DT systems presents several significant challenges. These challenges are examined in detail below.

(1) Structural Complexity in Data Integration: The integration of multi-source agricultural data necessitates addressing critical issues related to data format standardization,

protocol harmonization, and semantic interoperability. The disparate data structures and acquisition frequencies across different sources create substantial barriers to effective data integration and consistency maintenance within DT frameworks. For instance, the fusion of real-time sensor data streams with periodic satellite remote sensing imagery requires sophisticated solutions for data format transformation, temporal synchronization, and spatial registration. The diverse encoding schemes and data structures employed by different sensor types necessitate computationally intensive conversion processes to achieve unified data formats. Furthermore, the temporal synchronization of data streams from sensors and satellites with different time references requires precise temporal calibration to ensure chronological consistency [133,134]. Spatial registration presents additional challenges, requiring accurate alignment between the geographic coordinate systems of satellite imagery and the local coordinate frameworks of sensor networks to prevent spatial data misalignment. The inherent discrepancies in temporal and spatial scales across different data sources further exacerbate the complexity of data integration processes.

(2) System Complexity in Agricultural Ecosystems: Agricultural systems typically comprise multiple interdependent subsystems, including irrigation networks, nutrient management systems, and crop growth monitoring systems, whose operational states and behaviors exhibit complex interactions. Achieving seamless data integration across these subsystems while ensuring the DT accurately represents the holistic system state constitutes a major technical challenge [29].

4.3. Modeling and Simulation Challenges

The construction of three-dimensional crop models represents a fundamental component of agricultural DT systems. However, the intricate morphological characteristics of crops, characterized by substantial variability across different cultivars, developmental stages, and environmental conditions, present significant challenges. This section examines these challenges from three critical perspectives.

(1) Absence of Standardized Modeling Protocols: The current landscape of crop 3D modeling suffers from a lack of unified standards and normative frameworks, resulting in substantial variability in modeling methodologies, data formats, and parameter definitions across different research initiatives and applications. Discrepancies in geometric representation, topological structure generation, and material property configuration further exacerbate model incompatibility issues, hindering model integration and data sharing. This limitation significantly constrains the large-scale implementation of agricultural DT [129,137]. Furthermore, the common practice of simplifying and idealizing crop growth processes to reduce modeling complexity often results in the omission of critical factors, thereby compromising model accuracy [138,139].

(2) Challenges in Precise Simulation of Crop Growth Dynamics: Crop growth dynamics are influenced by multiple interacting factors, including climatic variables, edaphic conditions, and biotic stressors. The accurate simulation of crop microstructures and physiological processes presents formidable technical challenges, particularly in maintaining model consistency across diverse environmental conditions [140,141]. Current computational models are limited by processing capabilities and algorithmic precision, hindering realistic microscopic-level simulations. Although advanced data acquisition technologies, including 3D LiDAR systems and high-resolution imaging, have emerged for DT construction and real-time state updates, these approaches demand substantial computational resources and sophisticated algorithmic frameworks [91].

(3) Challenges in Model Validation and Assessment: The validation of 3D crop models faces significant empirical data acquisition challenges. Agricultural production systems are inherently influenced by seasonal and climatic variability, making repeated

experimental validation both costly and time-intensive. Furthermore, the absence of a standardized model evaluation framework complicates comparative assessments of model performance. Existing evaluation methodologies often focus on disparate aspects, with some emphasizing visual fidelity while others prioritize yield prediction accuracy, resulting in inconsistent and often incomparable assessment outcomes. This lack of a unified evaluation metric system hinders objective quality assessment of crop models [12,45].

4.4. Physical-Virtual Integration Bottlenecks

The fundamental paradigm of DT technology relies on establishing a bidirectional data exchange mechanism between physical entities and their virtual counterparts. However, the practical implementation of agricultural DT encounters several significant challenges in achieving effective fusion between physical and virtual models. These challenges are examined in detail through two critical aspects.

(1) Issues in Feedback Mechanism Accuracy and Reliability: The implementation of effective feedback mechanisms from virtual to physical systems is essential for successful DT applications. DT systems must not only monitor and simulate the state of physical entities but also actively influence these states through robust feedback control mechanisms [12]. The realization of such feedback systems requires high-fidelity models and reliable control architectures [45]. For instance, in controlled environment agriculture, DTs are expected to optimize crop growth conditions through precise regulation of environmental parameters such as thermal conditions, humidity levels, and light intensity. Ensuring the precision and reliability of these feedback control systems presents a significant technical challenge that requires further investigation.

(2) Limitations in Communication Infrastructure: The real-time integration of physical and virtual models in agricultural settings necessitates robust, high-bandwidth communication technologies. However, rural areas frequently suffer from inadequate network infrastructure, characterized by insufficient coverage and limited bandwidth capacity, which hinders real-time data transmission capabilities. These communication limitations result in delays in transmitting physical system data to virtual models, compromising the real-time representation of agricultural production states and the effectiveness of decision making processes.

4.5. Full Life Cycle Management Challenges

The implementation of comprehensive life cycle DT services for crop systems represents a significant application domain within agricultural DT technology. However, the realization of this objective encounters multiple technical and operational challenges that require systematic resolution. This section examines these challenges through two critical aspects.

(1) Challenges in Life Cycle Model Construction: The development of accurate full life cycle models necessitates extensive datasets and sophisticated modeling frameworks. Crop development processes are influenced by a multitude of interacting factors, including climatic variables, edaphic conditions, and biotic stressors. Furthermore, sensor systems are susceptible to operational failures under extreme conditions. For instance, in northern agricultural regions, sub-zero winter temperatures induce soil freezing, rendering numerous sensors inoperative and preventing the acquisition of critical soil temperature, moisture content, and crop residue data during these periods [142]. The development of accurate life cycle models in such dynamic and challenging environments constitutes a crucial research priority.

(2) Challenges in Service System Integration: The integration of service systems across the complete crop life cycle presents substantial implementation challenges. The

life cycle encompasses diverse stages, from genetic data management during breeding phases to field operation data during cultivation, and post-harvest storage, logistics, and market data. Each stage exhibits distinct data structures, operational logic, and application requirements, often lacking comprehensive planning and coordination mechanisms [143]. Moreover, the provision of precise, customized services to heterogeneous user groups, such as individual farmers, agricultural enterprises, research institutions, agricultural cooperatives, demands advanced data analytics and intelligent decision support capabilities that current technological frameworks struggle to provide [57]. Individual farmers typically require straightforward, interpretable cultivation guidance and real-time field monitoring information; agricultural enterprises necessitate comprehensive production management and market analysis services; research institutions prioritize in-depth scientific investigation and model optimization; while agricultural cooperatives often require data sharing and collaborative platforms. The current limitations of DT systems in addressing these diverse requirements hinder the full realization of DTs potential in crop life cycle management.

4.6. Limitations

There are still some limitations to the full deployment of DTs in agriculture. One of the primary challenges lies in the high costs associated with the development, implementation, and maintenance of agricultural DT systems. Establishing a fully functional DT requires significant investment in hardware (e.g., IoT sensors, remote sensing devices, and high-performance computing infrastructure), software (e.g., AI algorithms, predictive modeling, and cloud computing services), and expertise (e.g., data scientists, agronomists, and system engineers) [144]. These costs can be prohibitive, especially for small-scale farmers and agricultural enterprises with limited financial resources [60].

In addition to financial constraints, the trade-off between the complexity of DT implementation and its potential benefits must be carefully evaluated. A crucial consideration is determining when it is economically and practically viable to adopt DT technology in agriculture. While the deployment of sensor networks, IoT devices, and data integration platforms can range from \$400 to \$600 per hectare, the potential gains—such as a 15–30% reduction in resource waste or a 10% increase in crop yield—may take several growing seasons to materialize [145,146]. For instance, studies have shown that integrating DT technologies in precision farming reduces input costs and improves productivity, with a Return On Investment (ROI) typically realized within 3 to 5 years [34]. However, such economic models often assume stable market prices and uninterrupted technology performance—factors that may not hold in developing regions [147,148]. Cost-benefit analyses suggest that DT adoption is most justified in high-value agricultural production systems where the potential gains from yield optimization, resource efficiency, and risk mitigation outweigh the costs [149,150]. Conversely, in low-margin, traditional farming operations, where profit margins are narrow, the ROI for DT implementation may be insufficient to justify the initial and ongoing expenditures [148]. In regions with limited digital infrastructure and weak data governance frameworks, the cost of deploying DTs often exceeds their perceived benefits, making alternative smart farming solutions, such as simpler IoT-based monitoring systems, more practical [119].

Given these constraints, future research and industry efforts should focus on developing cost-effective, modular DT solutions that can be scaled according to the financial and technological capacities of different agricultural stakeholders [151,152].

5. Future Directions

The previous section has listed some of the challenges in the agricultural DT. The following one will provide some research directions for these challenges and explores the potential of integrating FMs [153] and DTs.

Introducing deep learning to crop modelling: Future research may focus on integrating deep learning techniques with crop imagery to generate high-accuracy 3D models with minimal manual input. By utilizing multi-modal data, such as multispectral images and 3D scans, neural networks can be trained to automatically reconstruct crop growth stages and simulate future development under various environmental conditions.

Addressing crop harvest follow-up issues: Integrating post-harvest logistics (e.g., storage conditions, supply chain management) with the DT framework to create a holistic, end-to-end system. Using advanced algorithms to predict quality and market prices, DTs can offer insights not just on crop growth but also on post-harvest handling, packaging, and distribution.

Integrating DTs and FMs: FMs, which have shown success in fields such as natural language processing [154,155], computer vision [156], and robotics [157–159], can enhance predictive capabilities, decision making accuracy, and overall scalability of DT in agriculture [160,161]. With FMs coming into the limelight in recent years, the future of agriculture is poised for a profound transformation through the integration of DT technology with large-scale FM.

The potential for integrating DTs and FMs is as follows:

- **Enhanced Decision Making:** Combining DTs' real-time simulation capabilities with FMs' ability to interpret complex data can create highly intelligent DSS. For instance, a DT representing a farm could leverage an FM to analyze weather forecasts, soil conditions, and crop growth models to recommend optimal planting schedules, irrigation strategies, and pest management plans.
- **Scalable Resource Optimization:** FMs can process multi-modal data from DTs, including sensor readings, satellite images, and historical trends, to identify resource optimization strategies. This integration could enhance predictions for water usage, fertilizer application, and energy efficiency at both micro and macro scales.
- **Predictive Analytics and Proactive Interventions:** DTs can simulate potential agricultural scenarios, such as pest outbreaks or extreme weather events, while FMs enhance predictive analytics by learning from large datasets. This enables proactive measures to minimize crop losses and mitigate risks.
- **Personalized Farming Solutions:** The ability of FMs, adapting their output based on specific contexts, can provide personalized insights for individual farms, thus complementing the capabilities of DTs in precision agriculture. These systems could recommend crop varieties, market trends, and customized farming techniques, aligned with specific goals such as maximizing yield or minimizing carbon footprint [161].

Even though there are many benefits of integrating DTs and FMs, it also comes with many challenges, such as model interpretability and trustworthiness, constraints of computational resource in agriculture, data privacy issues. By focusing on these key challenges and continuing to innovate, researchers and practitioners can pave the way for a more resilient and sustainable agricultural future through the fusion of DTs and FMs.

6. Conclusions

The integration of DT technology into agriculture represents a pattern shift toward data-driven, precise, and intelligent farming. This review has systematically examined the development, key technologies, applications, and challenges of agricultural DTs, pro-

viding a comprehensive overview of its potential to enhance agricultural productivity and sustainability.

One of the most significant contributions of DTs in agriculture lies in their ability to enable real-time monitoring, predictive analytics, and decision support. By leveraging multi-source data ranging from IoT sensors and remote sensing imagery to climatic and soil condition databases, DTs enable farmers to implement precision agriculture strategies effectively. Applications in crop production management, livestock monitoring, disaster prediction, and agricultural machinery optimization demonstrate multiple usages of DTs in modern agriculture. Furthermore, the development of advanced 3D modeling and simulation techniques has enhanced the accuracy of virtual agricultural environments, allowing for more precise forecasting and scenario analysis.

Despite these advances, several technical and operational challenges still exist. Data acquisition remains a fundamental obstacle, while issues related to data heterogeneity, sensor calibration, and collection inefficiencies limit the reliability of DT systems. In addition, agricultural data integration poses significant difficulties due to fragmented data sources, inconsistencies in data formats, and interoperability constraints between different platforms. The standardization and accuracy of 3D crop model construction require further refinement, as discrepancies in the data representation can lead to suboptimal simulation results. Moreover, the integration of physical and virtual models in agriculture remains an intricate challenge, demanding seamless synchronization between real-world agricultural processes and their digital counterparts. Finally, the implementation of a full life cycle DT for crops and related services are necessary robust frameworks for long-term data storage, processing, and analysis, ensuring that DT systems can support continuous decision-making and adaptive learning.

To address these challenges, future research should focus on improving data standardization, advancing AI-driven data fusion techniques, and enhancing the scalability of DT applications in agriculture. The integration of DTs with FMs may further revolutionize the sector, enabling more autonomous, transparent, and resilient agricultural ecosystems.

Author Contributions: Conceptualization, R.Z. and Q.M.; methodology, R.Z.; investigation, R.Z., H.Z. and Q.C.; writing—original draft preparation, R.Z.; writing—review and editing, R.Z. and Q.M.; visualization, R.Z., H.Z. and Q.C.; supervision, Q.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (Grant No. 62176106) and the Project of Faculty of Agricultural Engineering of Jiangsu University (Grant No. NGXB20240101).

Institutional Review Board Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

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