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Review

Digital Twins in Agriculture: A Review of Recent Progress and Open Issues

Li Wang

College of Economics and Management, Qingdao Agricultural University, Qingdao 266109, China; wliacademic@gmail.com or lilywang@qau.edu.cn

Abstract: Digital twin technology is expected to transform agriculture. By creating the virtual representation of a physical entity, it assists food producers in monitoring, predicting, and optimizing the production process remotely and even autonomously. However, the progress in this area is relatively slower than in industries like manufacturing. A systematic investigation of agricultural digital twins' current status and progress is imperative. With seventy published papers, this work elaborated on the studies targeting agricultural digital twins from overall trends, focused areas (including domains, processes, and topics), reference architectures, and open questions, which could help scholars examine their research agenda and support the further development of digital twins in agriculture.

Keywords: digital twins in agriculture; research progress; reference architecture; open issues

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1. Introduction

Technology has been changing the world. Gone are the days when value creation relied merely on manual labor and personal experience, especially with technologies like artificial intelligence, machine learning, and digital twins making rapid progress in recent years. Out of them, digital twin technology has attracted increasing attention as it enables adopters to keep their eyes on the business situations, predict the outcomes, and make better decisions from a digital-twinned environment. IoT analytics [1] reported that nearly 30% of global manufacturing companies have fully or partly used digital twin strategies. The digital twin market is expected to rise from $10.42 million in 2022 to $204.56 million by 2031 [2].

Like other emerging technologies, digital twins also brought a new field to various industries, and agriculture is no exception. Like a time machine, digital twin technology enables users to grasp their farms' past, present, and future, removing the uncertainties in agricultural production and management to some extent. Consequently, this new technology could firmly support the effective transition towards Agriculture 4.0 [3] and the industry's sustainable development, which will advance food security. In recent years, tech giants such as Microsoft and Siemens have actively made digital twins reach agriculture. Scholars also started to approach related topics. However, it is noticeable that there is still not much research, or rather published work, on this topic. Most digital twins in agriculture are still at the conceptual or experimental stage [4]. Before practical application, there are still a lot of problems that should be dealt with. For example, sensor data are hard to obtain in agriculture, almost all the virtual representation methods have their limitations, and agricultural digital twins often cost a lot. In order to achieve a leap in agricultural digital twins, it is crucial to summarize the existing research, identify the research progress, and offer insights into the future targets, calling on scholars to focus on and conduct in-depth research. Therefore, a thorough literature review is necessary.

Agriculture is a complex and diverse field with various long value chains from the initial sowing to production, distribution, and finally to fork. Each process or sector has its unique features, which should be fully considered when building digital twins. Looking back to the previous studies, we can find that some scholars have been making efforts (e.g., [5–9]). Most of them concentrated on a specific but limited production process or sector, such as irrigation and horticulture, calling for a comprehensive and comparative study. Additionally, the review should reflect the latest research progress. After reviewing the earliest studies, Pylianidis et al. [8] noticed that "digital twins have not been established in agriculture yet". From 2017 to 2020, digital twin technology adopted in agriculture was in its early stage of development. Some landmark works were frequently cited even in today's research. However, researchers never stopped expecting and striving for digital twins' applications in this field in recent years (e.g., [10–12]). Thus, it is necessary to look into the progress that has been made on the digital twin in agriculture after 2020, which has not yet been elaborated on by most existing review papers. Based on the above, when conducting the literature review of agricultural digital twins, we paid more attention to two aspects: the differences between various sectors and the latest work after 2020. To put together all the pieces, this work proposed and would answer the following four research questions.

RQ1: Which domains or processes have researchers introduced digital twins into?

RQ2: What topics had received much attention?

RQ3: How did the current digital twin architectures build?

RQ4: What are the open questions for digital twins in agriculture?

By addressing those four questions, this paper could make threefold contributions. First, we outlined the areas of interest and offered an in-depth investigation of current digital twin technology's role in agriculture and the differences between different sectors. Second, this study reviewed the digital twin architectures in the current documents, offering a technical basis for future study. Finally, we identified the topics or processes that require further discussion, such as data acquisition and ownership, which could give insights to researchers, technology practitioners, and stakeholders interested in the agricultural digital twins.

1.1. Digital Twin Concept

Digital twin technology is quickly expanding its influence in many areas, but there is still no consensus about who proposed this concept. A possible reason is that the digital twin was initially introduced without a name [13]. Some scholars believed that NASA took the lead [14,15], some considered the Air Force Research Laboratory (AFRL) as the pioneer [16], while many scholars claimed that the origin of digital twins is attributed to Grieves [12,17]. Tracing history, we can see that NASA or AFRL was the first to clearly put forward the "digital twin" [18,19] (Based on the existing materials, "digital twin" first appeared on NASA's *Draft Modelling*, *simulation*, *information technology & processing roadmap Technology Area 11* [18]. However, a presentation by Kobryn and Tuegel [19] claimed that AFRL had mentioned "digital twin" at the CBM+SI Workshop in Feb 2009. That is why we use "NASA or AFRL"). NASA's contribution was also recognized by Grieves [13]. Either NASA or AFRL proposed the digital twin concept for monitoring the conditions of a space vehicle, while Grieves [20] brought it (named the Mirrored Spaces Model in that research) into a broader field—product lifecycle management and gave the principles behind the digital twin vision [15].

With the application in various fields, like automotive, manufacturing, healthcare, and education, digital twins have been explained from different perspectives [9,21,22]. It is commonly agreed that a digital twin is the digital equivalent of a physical entity and its context, to which it is both in real time and remotely connected [15]. Accordingly, a digital twin reference architecture contains at least three main parts: physical entity, virtual entity, and the connection between them. Based on the virtual counterparts, the digital twin application users could monitor, optimize, and even predict real-world objects. To better achieve those goals, researchers strived to optimize the digital twin reference architecture and leverage innovative approaches (e.g., [12,23,24]), which will be elaborated on in Section 4.

1.2. Typology of Digital Twins

Different digital twins may serve distinct control purposes. To better investigate them, scholars have developed the typology of digital twins (e.g., [8,15,25–27]), which offers a theoretical basis for understanding the status of current agricultural digital twin applications later in this study. To date, there are four representative classification methods.

Level of data integration. One of the most well-known is Kritzinger et al.'s [26] three types, including digital model (DM), digital shadow (DS), and digital twin (DT). It was based on the level of data integration between the physical entity and its virtual counterpart. The integration level increases from DM to DT, and DT realizes a full data integration between two entities in both directions.

Technology readiness levels (TRL). This method assesses the maturity level of a certain technology, which is not only applicable to the digital twin technology. Explanations from NASA and the European Union are both representative. When reviewing the digital twin use cases in agriculture, Pylianidis et al. [8] introduced the European Commission's TRL scale [28]. They re-sorted the nine levels into three generic levels, including the conceptual phase (i.e., TRL 1–2; a conceptual digital twin), prototype phase (i.e., TRL 3–6; a digital twin with a working prototype), and deployed phase (i.e., TRL 7–9; a digital twin implemented in production).

Roles during the product life cycle (PLC). Digital twins are promising in product lifecycle management. Verdouw et al. [15] divided digital twins into six categories according to the usage phase. The imaginary digital twin offers a conceptual entity of an object that does not exist in real life. The monitoring digital twin digitally describes an existing physical object's actual state, behavior, and trajectory. Predictive digital twin shows a digital representation of a physical object's future states and behaviors via predictive analytics. Prescriptive digital twin is an intelligent digital entity that gives corrective and preventive suggestions on the physical objects based on optimization algorithms and expert advice. The autonomous digital twin can operate autonomously and control a physical object without human intervention. It could be self-adaptive and self-diagnostic. Recollection digital twin saves the complete history of a physical object that no longer exists in real life.

Hierarchical levels. Tao et al. [27] introduced Guo and Jia's classification from the perspective of hierarchy. Three different levels are the unit level, system level, and system of systems (SoS) level. The unit level means the smallest unit of an interested activity, like a piece of equipment in manufacturing activities. By integrating multiple unit-level digital twins, the system level can be generated. For example, a production line consists of unit-level factors, such as equipment and material. The SoS level can support cross-system interconnection, interoperability, and collaborative optimization.

When answering the research questions later, this study would focus on the last three classification methods because the technology readiness level can somewhat reveal the progress made by recent studies, and the other two methods, i.e., roles during the PLC and hierarchical levels, will reflect the construction of current agriculture digital twins.

2. Materials and Methods

This study obtained the final documents following two stages. In the first stage, relevant literature was searched on Google Scholar and SCOPUS. Then, we amplified the document set via the reference list of the downloaded literature. In the second stage, a final database was determined according to the selection criteria.

2.1. Data Collection

Digital twin technology is not a very new concept. Verdouw et al. [15] found that some applications are already in agriculture, but they were not framed as digital twins. To ensure the accuracy of the database scope, however, when collecting the literature, we only focused on the literature that clearly mentioned "digital twin", which was also applied in previous review articles (e.g., [4]).

On 26 December 2023, searches were conducted on Google Scholar and SCOPUS with the search string "Digital Twin" + "Agriculture". We downloaded the documents written in English. In this way, 153 papers were collected.

To avoid missing out on related works, we also went through the reference list of selected articles. The articles whose title clearly mentioned "digital twin" in the agricultural area could be carded. After deleting the duplicates, 23 articles were added, extending the literature database. The final selection, therefore, includes 176 publications.

2.2. Selection Criteria

This study narrowed the selection set further according to the following exclusion criteria.

First, after reading over the documents, we removed 17 works that did not directly focus on the digital twin in Agriculture.

Second, a quality assessment was conducted to ensure the article's quality. The journal papers should be published after a peer-review process and in the SSCI/SCIE journals. The conference papers must be published after a peer-review process, and only the statement on the conference website or final publication shall be the standard for determining whether a peer-review process has been carried out. If there is no explicit mention, we have to filter the document out. Based on that, 4 unpublished papers and 38 works not being published in the SSCI/SCIE journals were excluded, and 32 conference papers had to be discarded.

Third, since research after the year 2021 is our major concern, we further deleted the 13 papers published before 2021. The primary reason for removing those studies at this stage instead of filtering them out initially is to gain a deep understanding of the agricultural digital twin research before 2021 and their differences from the follow-up studies. Additionally, one conference paper and one book chapter that cannot be accessed were also deleted.

Based on the above, 70 documents were ultimately retained in the review database, including 43 journal articles, 25 conference papers, and 2 book chapters (see Figure 1).

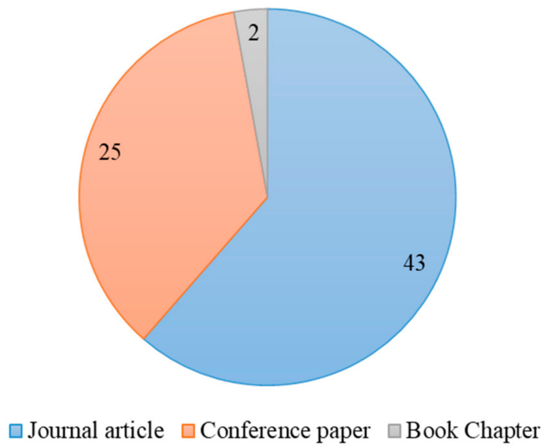

Figure 1. Types of published works in this study. Note: Those published at the conference first, but compiled as a book chapter afterward, were categorized as the conference paper.

3. Trends, Domains, and Topics of Digital Twins in Agriculture, 2021–2023

To answer RQ1 and RQ2, this section first gave an overview of papers published from 2021 to 2023. Then, we discussed their core foci, including the domains and topics. Through them, we can track the status and trends of digital twins in agriculture.

3.1. An Overview of Published Papers

Figure 2 counts the number of published papers per year. Less than thirty high-quality works are published each year, indicating that the agricultural digital twin is still in its infancy. Many issues are still awaiting exploration, resulting in an annual increase in the quantity of literature.

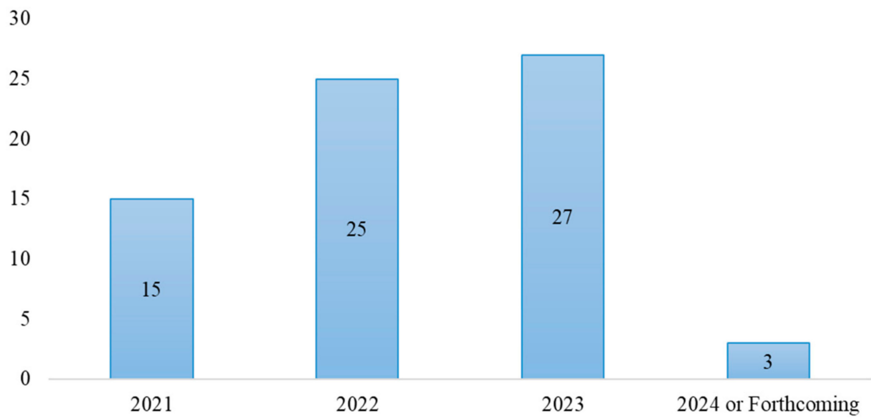

Figure 2. Number of published works per year after 2020.

As mentioned above, digital twins have not been established in agriculture yet before 2020 [8]. That means although digital twin technology benefits agriculture, most of the modeling or architectures remain in the conceptual phase, far from being implemented. A document classification is necessary in order to inspect the situation after that period. First, we grouped the literature into three categories: digital twin framework-related research, review, and others that are almost qualitative research. Second, we evaluated the maturity level of the digital twin frameworks in the collected studies according to the European Commission's TRL scale which was re-sorted into three categories, including Concept, Prototype, and Deployed level [8]. Figure 3 presents the final publication types.

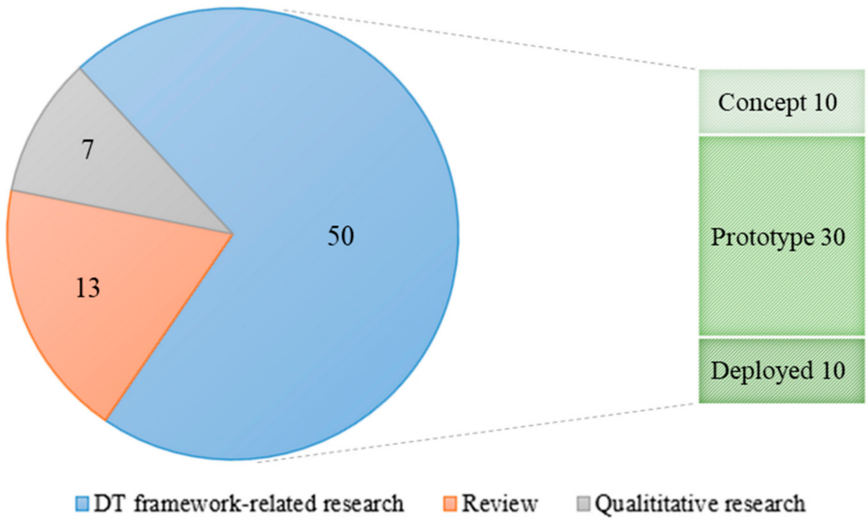

Figure 3. Distribution of publication types.

Fifty documents contributed to the digital twin framework. Compared with Pylianidis et al. [8], studies only proposing an idea and those applying the digital twin in the operational environment remained almost unchanged in quantity but both decreased in proportion. On the other hand, research that brought digital twin ideas into the lab or relevant environment has grown significantly in recent years, indicating digital twin applications' promising progress in agriculture. However, the validation and application of agricultural digital twin cases were often limited to a small-scale setting with only a few factors considered. Thus, the comprehensive test in a large-scale context still needs to be carried out.

For other publication types, the amount of review articles increased, and most of them particularly targeted a specific agricultural sector or process, implying the penetration of digital twin in agriculture. In addition, we found some pure qualitative studies that did not investigate the digital twin framework. However, some of them were no longer merely figuring out the definition of digital twin but have noticed the pending issues, such as simulation sickness when using digital twin-assisted tools (e.g., [22]).

3.2. Domains Received Attention

Section 3.1 concluded that the digital twin is expanding its influence in various agricultural sectors or processes. To identify the trends of applications, we further classified the documents according to the thematic cluster (see Figure 4).

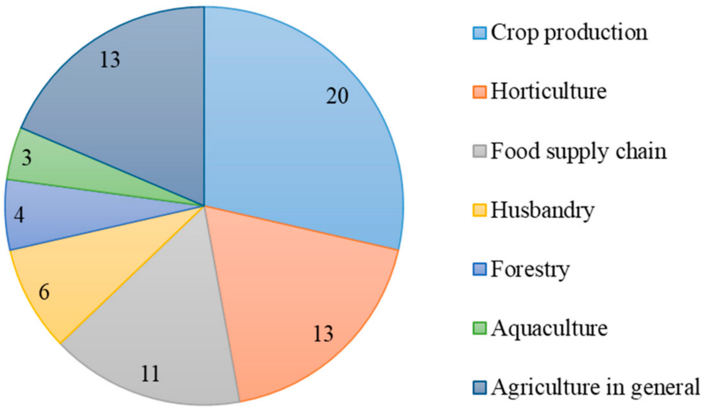

Figure 4. Agricultural domains mentioned in 2021–2023 studies.

The types of publications in different thematic clusters are distinct. According to Figure 5, prototype research almost dominates each domain.

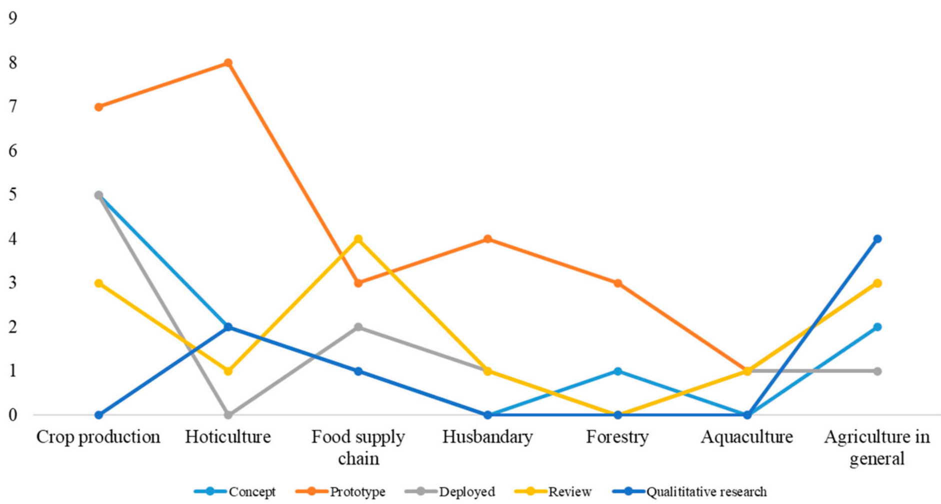

Figure 5. Types of publications in different agricultural domains.

3.2.1. Controlled Growing Setting, including Horticulture and Food Supply Chain

Agriculture is a highly complex and dynamic industry. Compared with production in the manufacturing or service industries, that process in agriculture depends more on natural conditions, like soil conditions, weather, and seasonal variation. The objects of labor (e.g., plants and animals) may take on a new form in the next second. Thus, developing agricultural digital twins would meet significant challenges, while a relatively stable setting can be simulated more easily. That could explain why controlled growing settings, such as horticulture and food supply chains, lead the way in agricultural digital twins at the current stage.

Horticulture. Greenhouses and indoor farming, like plant factories and aquaponics, have received much attention. According to the research focus, related studies that proposed a digital twin framework can be divided into two streams: **(1) studies on the growing status and process of plants** [29–32]. Using digital twins, scholars aimed to monitor and/or predict plant growth. Asfarian and Wulandari [29] focused on watering and fertilizer of smart aeroponic potato cultivation. With in-farm sensor networks, the back-end database system in the cloud, and a front-end module based on sensor data, the platform can monitor and visualize the potato's actual condition. Ghandar et al.'s [30] simulation of aquaponic installations at the smallest scale of a production unit can represent and predict fish growth. Howard et al.'s [31] digital twin framework can monitor and predict the greenhouse production process flow from cutting arrival to shipment. Spyrou et al. [32] proposed and tested a digital twin reference architecture for pharmaceutical cannabis production. However, they used data from sensors in greenhouse production facilities of different crops instead of cannabis. **(2) Studies on the growing environment of plants.** Different from the industrial field, plants in agriculture are even sensitive to each environmental parameter [33]. Digital twin technology is promising in keeping a healthy growing environment for plants [33–35] and more effectively leveraging energy to achieve sustainable development [36–38]. For example, Isied et al. [34] explored how to meet the solar greenhouse's power generation level and photosynthetic power absorption. To do so, they enabled the digital twin framework with a geometric ray-tracing algorithm and genomic-based optimization techniques to optimize a greenhouse's geometry, translucency, and material characteristics. Zhang et al. [33] collected multi-environmental parameters of the leafy vegetable plant factory and established the digital copy. The system helps managers adjust relative variables according to the stages of plant growth. Hull et al. [36] leveraged temperature monitoring instruments and the SVR algorithm to build a thermal model. This data-driven model can accurately predict a one-hour temperature inside a greenhouse tunnel, which allows users to make better decisions in terms of resource usage. Liu et al. [37] validated the plant factory designed with a digital twin, which could continuously measure the power consumption and represent it by a color-coded gradient map.

Apart from the above studies on the digital twin framework, there are three other studies. One of them reviewed the digital twin applications in greenhouse horticulture before early 2021 [5]. They finally found eight papers explicitly dealing with the digital twin in this area. Coupled with studies implicitly doing that, they concluded that most research described the monitoring type of digital twins. Based on the above, however, we can see that many studies after 2021 have started to look beyond it. The other two studies belong to the qualitative studies. Defraeye et al. [39] gave insight into how digital twins benefit the postharvest supply chain of fresh horticultural produce. Slob et al. [22] noticed that the simulation sickness might challenge the prolonged and regular use.

Food supply chain. Most studies in this area have considered multi-phases and even stakeholder relationships, indicating a high granularity level. Scholars harnessed digital twins to visualize and control food conditions, optimize decisions, and improve the information interaction among actors in the supply chain [40]. For example, digital twins assisted Burgos and Ivanov [41] in analyzing the influences of the COVID-19 pandemic on the food retail supply chain and improving its resilience. With data from open literature and actual breweries, Koulouris et al. [17] simulated the brewery process from brewhouse, fermentation to filling on SuperPro Designer v11. They also discussed the challenges and opportunities in food processing industries. From the holistic perspective, Valero et al. [42] took eight sectors of the meat supply chain into account, including land management, animal management, food processing, food products and packaging, transportation, retail, household and hospitality, and waste management, and established a conceptual digital twin framework. Based on two datasets obtained in 2018 and 2019, Shoji et al. [43] created virtual representations of imported fruits. They followed them from suppliers to distribution centers and finally to retail stores, which helped them identify the key factors influencing fruits' quality, like shipment period. There are two use cases that can be sorted into the "deployed" level. Both of them were designed by Maheshwari et al. [44,45] based on a highly industrialized ice cream making company. Maheshwari et al. [44] concluded that compared with the traditional method, the digital twin application improved the production performance; they further developed a digital twin reflecting the procurement, production, and distribution processes to optimize their performance [45].

Four review articles and one qualitative study also contributed to this domain. Singh et al. [24] identified fifty key determinants of digital twins in the food supply chain to enhance its resilience and sustainability, which could pave the way for model creation. When Tebaldi et al. [46] reviewed papers before August 2020, they found that specific literature is lacking, and monitoring might still be digital twins' primary position currently [21,40], but based on the above, we can find that documents after 2020 do make some progresses and expand the digital twin's function into optimization and prediction. Overall, research in this area is relatively leading and more systematic. However, some issues need to be carefully considered. For example, van der Burg et al. [47] brought up questions worth noticing in the agri-food domain, such as privacy issues and unintended consequences caused by digital twins.

3.2.2. Crop Production

Studies in this area have discussed the possibility of digital twins in many processes of crop production. In addition to three review articles, all the remaining studies aimed to design a digital twin framework (see Figure 6). We found that plant monitoring and irrigation caught much more attention; four out of five deployed use cases were all from irrigation, revealing that research on this topic currently precedes. Only a little research attempted to investigate the multi-processes or other processes. For example, Edemetti et al. [48] used sensor-equipped UAVs instead of sensors in the field to offer a 3D digital model of the vineyard. With this platform, farmers can check the physical vineyard out remotely, make data-driven decisions, improve profitability, and even decrease energy waste.

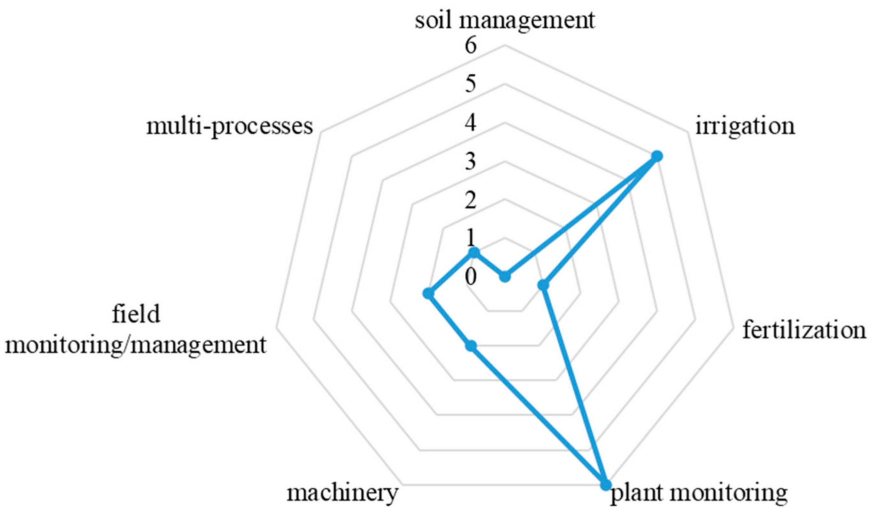

Figure 6. Designed digital twins for different crop production processes.

Plant monitoring. Three studies on plant monitoring belong to the concept type [49–51] and two to the prototype type [23,52]. **(1) Studies as the concept type.** Majore and Majors [49] designed a digital twin solution for organic potato production and applied it to four places in Latvia. We only had to classify it into the concept type because they did not give the testing results. However, it is worth noticing that this study considered the growth processes from potato's establishment to maturity. Skobelev et al. [50] developed a digital twin of crop. By analyzing external environmental parameters, like climate and soil types, it can plan crop growth, predict yield, and make recommendations. Their further study especially focused on winter wheat [51]. **(2) Studies as the prototype type.** Li et al. [23] applied deep learning in leaf reconstruction to improve the digital twin system for plant growth. This new approach has higher accuracy and predictive results, allowing the recovery of the leaves from a single view. Skobelev et al. [52] developed an intelligent system of the plant digital twin. According to weather and climatic conditions and external events, the functions—modeling duration of plant growth and forecasting yield—have been implemented.

The above shows that scholars have tried to consider more plant growth processes and develop their digital twin architectures. However, only the limited units or functions could be examined when bringing them into the lab environment. A possible reason lies in the dynamicity and complexity of crop growth.

Irrigation. The demand for freshwater in agriculture is increasing, while the use of freshwater in this area is often inefficient [11]. Accordingly, the current literature had a common goal of leveraging digital twins to tackle this issue, and some of the solutions had been implemented on a small scale. We finally sorted two use cases as the prototype [11,53] and four as the deployed [3,54–56]. **(1) Studies as the prototype type.** Alves et al. [53] validated a digital twin system for monitoring and automatically controlling the irrigation system. Manocha et al. [11] proposed a digital twin-based irrigation approach to predict soil moisture for the upcoming days and give irrigation suggestions based on sensor data, including soil moisture, humidity, and temperature. **(2) Studies as the deployed type.** Tsolakis et al. [3] combined the digital twin and UAVs to monitor the water stress in orchards. They simulated the orchard layout, inside trees, a UAV with sensors and cameras, and conducted a pilot test in an orchard. Bellvert et al. [54] successfully adopted the digital twin-supported automated irrigation scheduling at a commercial vineyard in Aranyó. The framework calculates water requirements and automatically arranges the irrigation by assimilating in the nearly real-time estimation of fIPARd. Moreira et al. [55] held that the digital twin could improve the collective irrigation system (CIS). They proposed a system of primary and secondary pressurized CIS network and executed a field test in Southern Portugal. Thapa and Horanont [56] introduced a digital twin-based zero-energy farm with a drip irrigation system using data from a 1200-square-meter farm in Thailand. The application allowed users to remotely access the information to monitor and control the farm manually or by setting a timer or automatically.

Other processes, including fertilization, machinery, and field monitoring/management. Corresponding studies show that various uncertainties and scenarios must be considered when applying digital twins in agriculture again. The smart agriculture framework can support the fertilization decision through nitrogen management in crops, but it must be tailored to local conditions [57]. Foldager et al. [58] developed a model for agricultural vehicles in the open-source multi-physics code. They attempted to figure out the effects of the field condition—terrain in two settings, i.e., different track widths and loading and unloading, via simulations. Kaburlasos et al. [59] tested a grape-harvesting robot hand's capacity by grasping different objects. Kalyani [60] united microservices and multi-agent systems to develop a digital twin conceptual architecture, especially for winter wheat. The system can mainly realize two functions: farm access service and field management. Khatraty et al. [61] argued that the source of data should be consistent. They innovatively leveraged and compared two sources of data (i.e., IoT sensors collected weather data and satellite data) to keep the field management decisions more accurate.

For the remaining three review articles, Melesse et al. [62] presented the approaches, adoption levels, and challenges of crop predictive monitoring with digital twins. They found that digital twins for this process are still in the lab stage. Nasirahmadi and Hensel [14] offered a general framework of digital twins in multi-processes of crop production; Silva et al. [63] reviewed studies on applying digital twins in soil quality assessment.

Both studies agreed that soil management called for a more thorough exploration. These conclusions still can be found in this study, indicating that the diffusion of digital twins in crop production is generally slow.

3.2.3. Domains, including Husbandry, Forestry, and Aquaculture

Livestock farming can be improved by digital twins in many aspects, like energy management, growth management, animal status understanding, and disease prediction [7]. In the collected database, documents mainly focused on two aspects: **(1) energy management.** Purcell et al.'s digital twin model [64] has a high precision in measuring the herbage mass of the grassland. Their study proved the feasibility of a digital twin for grassland management to reduce related labor requirements. Jeong et al. [65] paid attention to the energy management of pig houses. They created a virtual pig house and simulated the actual data from the physical one to find a solution with the highest energy efficiency. With data from bin stocks, Raba et al. [66] applied a computer-aided system to control and optimize the animal feed supply chain from feed mills to livestock farms. **(2) animal status understanding.** Han et al.'s [67] AI-enabled digital twin can monitor the physiological cycle of cattle in real time and forecast its next behavioral state with the LSTM model. Zhang et al. [68] proposed a digital twin architecture for the feeding behavior of dairy cows during their adult stage. They proved that the architecture could identify feeding and non-feeding behaviors at an accuracy rate of 95.07%.

Real-time monitoring forestry data are hard to obtain [69], making it hard to create a forestry digital twin. To better visualize the forest structure, Buonocore et al. [70] claimed that the individual tree is the core element. Their conceptual proposal aimed to record variables of the tree and its environment through real–virtual digital sockets. In that manner, the digital twin can report the health status of forests and ultimately achieve sustainable forest management. Qiu et al. [71] graded the spatial structure of Chinese fir trees, leveraged various data like remote sensing data, and constructed a dynamic stand growth model. The framework can enhance the simulation of digital twins. Cirulis et al. [72] developed a BogSim-VR system for bog ecosystems or peatlands, which can give their 3D replicas and allow experiments with different human actions. Jiang et al. [69] used historical remote sensing images as the input of a machine learning-based digital twin. With the LSTM model, it can even effectively predict the forest's future image. However, none of the studies can be categorized as deployed, i.e., there is no study being demonstrated in the operational environment.

The application of digital twins in aquaculture is relatively low [9]. We only collected two studies that introduced digital twins to aquaponics. Zhao et al. [12] combined numerical simulation and artificial neural network to construct a digital twin for damage detection of fishing nets. The proposed framework can accurately detect the net damage at more than 93% under different wave conditions. Teixeira et al. [73] leveraged the virtual duplicate of aquaculture farms to monitor and control the water quality of its physical twin.

3.2.4. Agriculture in General

Some works did not focus on a particular sector in agriculture. They attempted to discuss the digital twin in a broader context, such as smart agriculture or even agriculture, which were thus sorted into "agriculture in general". Compared with other studies on a specific area, those in this domain contribute to more reviews (three works) and qualitative studies (four works). Regarding the review, Pylianidis et al. [8] found that until early 2020, digital twins had not been established in agriculture. They suggested that digital twin applications can begin with simple setups and be enhanced with more components. The other two reviews concentrated on the research status of digital twins in smart agriculture [74] and irrigation and smart farming [6], respectively. The remaining four qualitative studies have noticed some new issues in agricultural digital twins. Nie et al. [75] compared the usage of artificial intelligence (AI) and digital twins in agriculture and concluded that digital twins face many more challenges in this area than in other industries, including the complexity of data, and the realization of intervention-free simulation and interoperability issues. They also concluded that the development of digital twins and AI should be complementary, which was recognized by Liu et al. [76]. Their study emphasized the cooperation between digital twins and Generative AI in agriculture; generative AI can help overcome the challenges faced by digital twins. Rogachev et al. [77] pointed out that digital twins could pose threats, such as high costs, digital security, and unemployment. They held that only government agencies, scientific organizations, technology organizations, and agricultural organizations jointly work, and digital twins maximize their effectiveness. Purcell et al. [4] also warned that while bringing chances, digital twins exert adverse and unforeseen technical and social–ecological impacts, like wealth inequality, negative ecological feedback loops, and difficulties in maintenance. Such possible consequences should be considered early to achieve sustainable development. These works offered new insights into the development of the digital twin.

Six other documents discussed the design or application of agricultural digital twins. Perhaps because agriculture in general covers a wide range, however, the applications in practical environments only account for a small portion (one work, i.e., [15]). Five digital twin-enabled smart agriculture use cases were briefly mentioned, including arable farming, dairy farming, greenhouse horticulture, organic vegetable farming, and livestock farming [15]. From the basic information, we can trace the monitoring, prediction, and optimization functions of digital twins. The rest of the documents designed a conceptual framework or validated the possibility of their digital twin framework [78–82]. For example, Kalyani and Collier [80] introduced a fresh approach to integrate MAS and Cloud–Fog–Edge with digital twins that can be used in smart agriculture to monitor crop growth and manage farms better. Chukkapalli et al. [79] proposed that the monitoring function of digital twins can be vital in dealing with the security risks from Cyber-Physical Systems. They applied a digital twin-supported security surveillance framework to detect abnormal scenarios. Cho et al. [78] integrated Building Information Modeling and Geographic Information Systems to design a web-based digital twin to visualize the agricultural infrastructure.

3.3. A Further Investigation of Current Topics

Based on the above, we can find that from 2021 to 2023, digital twins in agriculture have received more attention than before. Although progress is still slow, most studies have focused on designing, examining, and demonstrating digital twins in various agricultural environments. The monitoring function dominates, but quite a few studies have constructed or validated the prediction and optimization functions. Additionally, some scholars also noticed the challenges of implementing related architectures, which pave the way for large-scale applications. The topics of current research can be mainly summarized into three aspects as follows.

(1) Manage the objects of labor to raise agricultural productivity. Studies often developed digital twin architectures to monitor the growth or behaviors of objects of labor (e.g., plant and animal) to help farmers understand their status in real time and remotely. According to that, farmers can make better decisions. Some studies started to predict the yield, provide recommendations, and even control the production system autonomously without human intervention. Objects of labor frequently mentioned include winter wheat, grape, potato, fresh food, cow, and tree, while many other studies had not clearly defined a certain kind of plant or animal.

(2) Focus on the means of labor to promote sustainable development. The demand for more land, fresh water, and energy is increasing to feed the growing population. However, resources for agricultural production are limited and currently unable to be effectively used. To address these issues, scholars leveraged digital twins to model the conditional elements of agricultural production virtually. The monitoring or prediction from the system can offer a basis for optimizing resource utilization. Solar energy and water resources are the key resources of interest.

(3) Discuss the challenges of digital twins in agriculture and formulate solutions. Related studies are often conducted from two perspectives. Some studies primarily discussed how to better design the digital twin framework. Except for introducing new methods to improve the virtual copy construction, the acceptance of farmers and the interaction between digital twins and human labor also gradually came into some scholars' view (e.g., [22,37]). Other studies mainly investigated the possible threats of digital twins and then gave corresponding suggestions.

4. Current Digital Twin Architectures in Agriculture

To answer RQ3 (i.e., How did the current digital twin architectures build?), we proceeded to list the digital twin frameworks built in the current literature database. The study first extracted the three main parts of a digital twin reference architecture, i.e., the physical entity, the virtual entity, and the connection between them. Especially, the connection involves the data source, input data, and technologies coupling the physical entity with the virtual one. We further categorized the frameworks from two perspectives, i.e., hierarchical levels and roles during the PLC. Table 1 details 50 works that proposed the digital twin model.

Based on the above 50 studies, we can construct a general and brief conceptual framework for digital twins in agriculture (see Figure 7). It should be noted that although previous studies have commonly accepted that digital twins consist of three main parts (i.e., physical entity, virtual entity, and the connection between them), there has been no consensus on the detailed layers of digital twin reference architecture, e.g., [11,32,53,61,68]. When drawing the framework, we referred to the more developed research on manufacturing digital twins, e.g., [83–85], carefully considering digital twin's concept and current studies on agricultural digital twins.

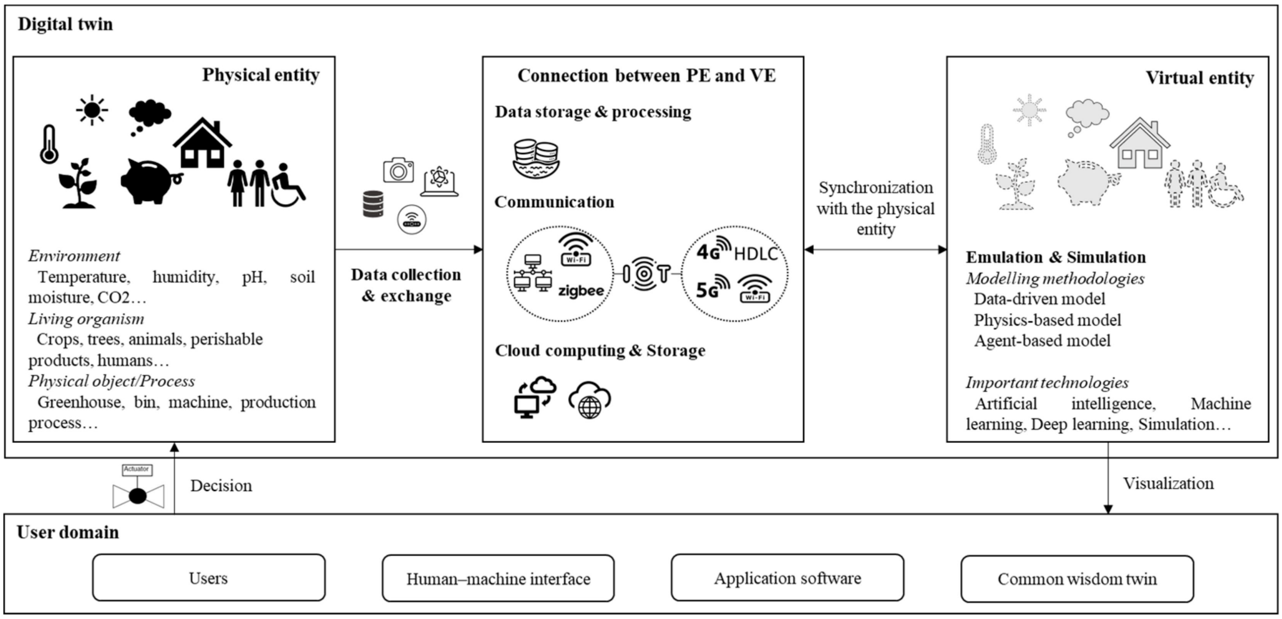

Figure 7. Architectural framework of agricultural digital twins.

Table 1. Overview of documents that designed the agricultural digital twins.

Citation	Physical Entity	Data Source	Input Data		Technologies Coupling PE and VE	Virtual Representation	Digital Twin Type								
			Sensor Data	Other Data			Levels			Roles during the PLC					
							U.	Sys	SoS	IM	MO	PD	PS	AU	RE
[58]	Agricultural vehicle	Sensors	Not specified, but mentioned operational data	N/A	Machine learning	Simulation		•		The design is still in the initial step of development.					
[52]	Plant (winter wheat in particular)	Available monographs and reference books	N/A	Air temperature and humidity, soil humidity, hydrothermal coefficient	Ontologies and multi-agent technologies	Dashboard		•			•	•	•		
[41]	Food retail supply chain	Data from supermarket, retail company, and Statista	N/A	Product demand, product price, inventory spending, locations	Simulation (anyLogistix)	Simulation			•		•				
[79]	Smart farm	Data collected by other scholars from sensors	Time, air humidity, air pressure, air temperature, light intensity, soil moisture	N/A	Ontologies, Cloud, PCA based anomaly detection model	Simulation		•			•				
[30]	Aquaponics unit	Sensors	pH, humidity, room temperature, light intensity, water temperature, water flows, dissolved salts	N/A	IoT, Raspberry Pi, Cloud, Machine learning, Simulation	Dashboard	•				•	•			
[17]	Beer production and filling facility (process)	Open literature and actual breweries	N/A	Operating conditions, timing, and resource consumption	Simulation (SuperPro Designer v 11)	Simulation		•			•		•		
[82]	Solar farm with 16 panels	Simulation	N/A	Panel inclination, refractive index of panels, dimensions of panels, shape of panels, ground refractive index, panel height above ground	Genomic machine learning	Simulation		•			•		•		
[3]	Orchard	UAV with sensors	Water stress of plant	N/A	Not specified	Not specified		•			•		•		
[55]	Pressurized collective irrigation system	GIS, weather station, field measurements	N/A	Water input, water delivery to the irrigation system, level variation in the reservoirs, energy consumed in electric pumps and recovered energy	IoT, cloud, hydrodynamic model	Simulation		•			•		•		
[15] (five cases)	Arable field	Sensors, GPS tracker	Not specified		e.g., FIWARE Orion Context Broker	Dashboard	Cannot identify based on the available information.				•	•	•		
	Cow	Sensors mentioned	Not specified		e.g., Cloud	Dashboard					•	•			
	Tomato greenhouse	Sensors mentioned	Not specified		e.g., Wi-Fi, cloud	Dashboard					•	•	•		
	Not specified	Sensors, weather station, etc.	Weed pressure, crop growth	Weather	e.g., WLAN	Dashboard					•	•	•		•
	Not specified	On-farm sensors and slaughterhouse data	Not specified		e.g., Wi-Fi, cloud	Dashboard					•	•			

Table 1. *Cont.*

Citation	Physical Entity	Data Source	Input Data		Technologies Coupling PE and VE	Virtual Representation	Digital Twin Type								
							Levels			Roles during the PLC					
			Sensor Data	Other Data			U.	Sys	SoS	IM	MO	PD	PS	AU	RE
[29]	Potato plant	Sensors	pH, light intensity, TDS, stereo camera, ultrasonic, water temperature, humidity, temperature, etc.	N/A	Edge Computation, Microcontroller, Cloud	Dashboard	•				•				
[70]	Forest	IoT devices, image sensing technologies, flux towers, field measurements, metadata	Tree variables (e.g., variables related to trees, the soil where the tree stands, and climate factors in the near space of the tree), forest variables (e.g., wildlife and herbivores, weather, air quality pollution)	Hydrological basin parameters, stand structure, species diversity, atmospheric gaseous and energy exchanges, forest inventories	Cloud computing, blockchain and smart contracts	Not specified		•			•				
[49]	Potato plant	Physical equipment mentioned (e.g., UAV)	Environmental factors (i.e., soil characteristics) and biological phenomena of the potato plant	Biological phenomena of the potato plant, but not specified	Not specified	Not specified		•			•		•		
[50]	Plant, taking winter wheat as an example	Filed sensors mentioned	Not specified, but including climate, weather, types and characteristics of the soil, biological features of the plant, etc.		Multi-agent technologies	Dashboard		•			•	•	•		
[51]	Winter wheat	Not specified	Not specified, but including air temperature, precipitation, relative air humidity, soil moisture, etc.		Ontologies and multi-agent technologies	Simulation		•			•	•	•		
[42]	Circular meat supply chain	Sensors	Not specified (only conceptual framework)	N/A	Microcontroller, Wireless communication technologies, Data Mining, AI, Machine Learning	Not specified			•		•	•	•	•	
[72]	Bog ecosystem	GIS, LIDAR data from a drone	Mentioned IoT network, but not specified	Amount of snow and rain, temperature, sun radiation, humidity, peat depth, etc.	Simulation, Virtual Reality	3D visual		•			•	•			
[48]	Vineyard	Sensor-equipped UAV	Weather conditions, sun exposure, amount of water, leaf conditions, fertilizer or fungicides use	N/A	5G, cloud, machine learning, AI	3D visual			•		•		•		
[34]	Solar greenhouse	Pysolar Python package	N/A	Number of light rays, ground refractive index, speed of light, solar panel thickness, generalized radii, geometric exponent	Simulation tools (e.g., HELIOS, Raytrace3D), genomic optimization algorithm	Simulation		•			•		•		

Table 1. *Cont.*

Citation	Physical Entity	Data Source	Input Data		Technologies Coupling PE and VE	Virtual Representation	Digital Twin Type								
							Levels			Roles during the PLC					
			Sensor Data	Other Data			U.	Sys	SoS	IM	MO	PD	PS	AU	RE
[67]	Cattle	Sensors	Cattle's status, e.g., resting, rumination, high activity, medium activity, planting (heavy breathing), grazing, walking	N/A	IoT, AI, deep learning (i.e., LSTM)	Not specified, but analyzed on the computer	•				•	•			
[31]	Horticulture greenhouse	Facility API, sensors, historical database	Compartment parameter	Indoor climate data, environment data, production planning data	Multi-agent-based simulation (AnyLogic in this study)	3D visual		•			•	•			
[69]	Forest image	Landsat 7 ETM + C2 L1 data set	Remote sensing images	N/A	Machine learning (i.e., LSTM)	Not specified, but analyzed on the computer		•				•			
[23]	Plant leaf	Self-collected datasets	Not specified, but including point clouds with normal vectors, RGB images		Deep learning (i.e., ResNet)	3D visual	•				•				
[64]	Pasture	Sensors	Grass and weather information	N/A	Grasshopper grass assessment tool, simulation (i.e., AgPasture grass simulation model)	Not specified		•			•				
[43]	Fruits, including cucumber, eggplant, strawberry, and raspberry	Sensors	Air temperature, geolocation	N/A	Simulation (continuum multi-physics model, COMSOL Multi-physics)	Not specified, but analyzed on the computer			•		•				
[35]	Hydroponic grow beds	Sensors	pH, electroconductivity, air temperature, water temperature, humidity, light intensity	N/A	IoT, Raspberry Pi, PHP, MySQL, GPIO	Dashboard	•				•	•	•	•	
[12]	Fishing net	Sensors	Data related to complete and damaged fishing nets, e.g., net length, net width, net solidity ratio, diameter of net twines, etc.	N/A	Simulation, machine learning (i.e., ANN)	Simulation	•				•				
[66]	Farm	Sensors	Bin stocks, served diet, breed size	N/A	IoT, machine learning	Dashboard			•		•	•	•	•	
[73]	Aquaculture farm	Sensors	Physico-chemical variables, water quality variables	N/A	IoT, AI	Dashboard		•			•	•	•	•	
[56]	Zero-energy farm with a drip irrigation system	Sensors	Environmental conditions, e.g., temperature, humidity, moisture	Geospatial data (not specified the source, but we may infer)	Simulation (i.e., EnergyPlus, DSSAT), Wi-Fi, MQTT, Raspberry Pi, AI	Dashboard			•		•		•	•	
[60]	Arable farming (winter wheat in particular)	Not specified	Not specified, but mentioned farm data and weather		Microservices and multi-agent systems	Dashboard			•		•	•	•		

Table 1. *Cont.*

Citation	Physical Entity	Data Source	Input Data		Technologies Coupling PE and VE	Virtual Representation	Digital Twin Type								
							Levels			Roles during the PLC					
			Sensor Data	Other Data			U.	Sys	SoS	IM	MO	PD	PS	AU	RE
[80]	Farms and fields used for Arable Farming (winter wheat in particular)	Sensors, third-party data sources	Parameters related to farms and fields	Weather, satellite, financial data	Not specified, but mentioned "integrating MAS and Cloud–Fog–Edge with Digital Twin"	Not specified			•		•	•	•		
[37]	Plant factory	Sensors, Cameras	Electricity consumed by air conditioner, ventilation, lighting, and humidifiers	360° environmental pictures	IoT, JSON	Virtual Reality		•			•				•
[81]	Not specified, but mentioned farm, crop, etc. in the crop management and sales	IoT systems	Not specified, but including soil quality, weather conditions, irrigation systems, crop types, crop quality, crop quantity, market prices, etc.		IoT, machine learning	Dashboard			•		•	•	•		
[53]	Irrigation system with its physical components	Field tests, external services, simulation	N/A	Soil data, weather data, and crop information	IoT, MySQL, Siemens Plant Simulation software, OPC UA, Orion Context Broker	Dashboard		•			•	•	•	•	
[78]	Agricultural area (i.e., a test bed area of a reservoir)	Filed surveys, photos captured by UAVs	N/A	Land shape, sluices, channels of the entire beneficiary area	DJI Terra software	3D visual			•		•				•
[36]	Greenhouse tunnel	Sensors	Temperature, humidity	N/A	Telegram and DropBox (for data collection), Raspberry Pi, Simulation, i.e., SVR	Simulation	•				•	•			
[65]	Enclosed pig house	Not specified, but mentioned sensing entities	Parameters related to environment, operation, and biometrics from a real pig house		Simulation (i.e., EnergyPlus and OpenStudio simulation software for building energy simulations)	Dashboard		•			•		•		
[59]	Robot hand	Human hand	N/A	Human hand grasping data	Parametric mathematical models implemented in software	Not specified	•			The design is still in the initial step of development.					
[61]	Rice field	Sensors, satellite	Precipitation, wind speed, temperature, air humidity	Overview of the field's state	IoT, deep learning	Not specified, but analyzed on the computer			•		•	•	•		
[44]	Ice cream manufacturing	Data from ice cream manufacturing company	N/A	Manufacturing parameters	Simulation (AnyLogicTM)	Simulation		•			•		•		

Table 1. *Cont.*

Citation	Physical Entity	Data Source	Input Data		Technologies Coupling PE and VE	Virtual Representation	Digital Twin Type								
							Levels			Roles during the PLC					
			Sensor Data	Other Data			U.	Sys	SoS	IM	MO	PD	PS	AU	RE
[45]	Procurement, production, and distribution of the ice cream manufacturer	Data from ice cream manufacturing company	N/A	Market demand forecasts, production capacity, procurement data	Mixed-integer linear programming, agent-based simulation, AI, machine learning, IoT	Simulation			•		•	•	•		
[38]	Enclosed indoor farm	Simulation	N/A	Aperture parameters (for light direction), source tube values, total power values	Genomic optimization, Simulation	Simulation		•					•		
[71]	Forest	UAV, field measurements	N/A	Individual tree indices (coordinates, tree age, diameter at breast height, etc.), neighborhood indices (uniform angle, openness, etc.)	Cloud, Bayesian, and grading theory	Virtual Reality		•			•	•		•	
[68]	Adult cow	Cameras, collars, and other sensor devices	Real-time location and neck movement data of the cow	N/A	SVM, KNN, LSTM	Dashboard	•				•		•		
[33]	Leafy vegetable plant factory	Sensors	Temperature, humidity, illumination intensity, soil humidity, TVOC concentration, CO_2 concentration	N/A	IoT (e.g., Wi-Fi), Simulation	Dashboard		•			•		•	•	
[54]	Irrigation sector	Sensors, weather stations, satellite, field measurements	Soil moisture, irrigation, precipitation events	Meteorological data, biophysical variables of the vegetation, actual evapotranspiration	TSEB-PT modeling approach, Penman–Monteith approach	Simulation		•			•	•	•	•	
[11]	Irrigation framework	Sensors	Soil moisture, humidity, temperature	N/A	IoT, Genetic algorithm, ANFIS	Simulation		•			•	•	•		
[57]	Cultivated area	GPS, yield prediction, GIS, RS, Sensors	Spatial variability of ECa, multi-spectral reflectance	Spatial variability of area, soil properties, crop growth and yield	Not specified	Not specified		•			•		•		
[32]	Pharmaceutical cannabis production process	Sensors (but not directly related to pharmaceutical cannabis, collected as other data)	N/A	CO_2, PAR, humidity deficit, dewpoint, temperature, etc.	3G/4G, Greenhouse LAN, Wi-Fi, JSON, API	3D visual		•			•				

Note: Data clearly labeled "collected from sensors" can be sorted as sensor data. The digital twin reference architectures were categorized based on the functions that had been realized rather than all the functions envisaged by the author(s), i.e., those that have not been realized at the current stage were excluded. PE: Physical entity; VE: Virtua entity. U.: Unit; Sys: System; IM: Imaginary; MO: Monitoring; PD: Predictive; PS: Prescriptive; AU: Autonomous; RE: Recollection. • marks true.

Figure 7 shows five layers in the agricultural digital twin, including data collection and exchange, data storage and processing, communication, cloud computing and storage, emulation and simulation (together with the user domain). In the **first layer**, information about physical entities, such as the environment, living organisms, and physical objects, was collected or exchanged between sensors, actuators, and the local controller or data acquisition devices. Data preprocessing should be performed to keep them accurate and available before modeling. The collected data are stored in the **local data repositories** that should connect with the local controller and data acquisition devices in the first layer and the IoT Gateway in the third layer both. The data will be transferred via the **communication level** (aka Data-to-Information Conversion Level [85]). By converting data collected in the first layer to information to be sent to the cloud-based information repository, this level links the second layer with the fourth layer. The communication level also supports real-time bi-directional and seamless communication between physical entities and their digital entities, indicating the significant role of IoT in the digital twin. The **cloud computing and storage level** includes cloud services that save historical information reflecting physical entities' status from the third layer. As Redelinghuys et al. [85] claimed, hosting the repositories in the cloud enables the agricultural digital twins to be more available, accessible, and connected. In the **emulation and simulation layer**, relevant software should be used to help users interact with this layer. Three methodologies to develop agricultural digital twin modeling can be summarized, including data-driven, physics-based, and agent-based models. For the data-driven model, technologies like machine learning and deep learning to represent the status and characteristics through collected data were receiving attention. For the physics-based model, observing actual phenomena gives a sound basis for mathematically incorporating them into virtual representation. The agent-based model, or rather ontological multi-agent model, is also a common method in this area. This model enables the usage of heterogeneous data, which helps identify patterns of physical entities' growth and development in agriculture [62]. Additionally, the emulation and simulation layer also offers users representation of the physical entities and their status, such as graphs on the dashboard, 3D visualization, and Virtual Reality. With it, users can evaluate the physical entities and make decisions.

The above description is usually for a unit-level digital twin. When building the system-level or SoS-level model, a hierarchical structure is necessary. Since each physical entity does not exist independently, how to better integrate all components and reduce the complexity should be noticed. Studies like Buonocore et al. [70] attempted to create hierarchical frameworks, but many remained in the conceptual stage.

Table 1 further reveals that the current digital twin reference architectures in agriculture have four significant features.

(1) The physical entity from the system or SoS level received increasing attention. Agriculture is a complex and diverse field. Thus, merely building a digital twin framework on individual plants or animals can hardly meet the demand. However, previous studies seldom looked beyond plants or a single production unit ([5], the study reviewed greenhouse horticulture digital twins). Similar results can be obtained in this review—the current studies still mainly focused on a certain process or a single production area; it is more common to mark "not specified" among the research considering system-level and SoS-level digital twins as some of them only proposed a conceptual framework or idea. Yet, compared with earlier research, more and more studies have started to design the digital twin architecture at the system and even the SoS level. That means scholars are applying the digital twin to agriculture from a broader perspective, such as the entire crop growth process, beer production line, and food supply chain from suppliers to retailers, making the digital twin expand its influence in the agricultural sector.

(2) According to Qiu et al. [71], compared with technologies like XR and CAVE2, digital twin enables two-way interaction and virtual–real synchronization, but it depends on the reliability and stability of IoT and sensor data. Table 1 shows that in the current studies, input data mainly came from environmental sensors, which precisely signals real-time

changes of the relatively static physical entities. However, much research also analyzed the growth behaviors or statuses of living plants or animals based on environmental information. That might lead to low accuracy of virtual representation and communication. As a result, some scholars chose to add external databases, such as third-party data and field surveys, but it is worth noting how to deal with the distinctions between different data sources. Other scholars tried to obtain data directly from the living object (e.g., [67,68]), but the related model requires plenty of data. Therefore, obtaining sufficient data and properly preprocessing them is necessary. Additionally, offering essential models and methods representing the growth and development of living organisms also needs to be solved [51]. Taking crops as an example, Skobelev et al. [51] suggested that crop variety and characteristics should be considered. That could also explain scholars' efforts to provide new methods for better virtual representation of plants or animals from the unit level (e.g., [23]). As Asfarian and Wulandari [29] claimed, the digital twin platform can initially be formed from the unit level and then improved to higher levels.

(3) Scholars are introducing emerging technologies such as AI and machine learning to support better matching between physical entities and virtual ones. One of the direct results is that the number of predictive and autonomous digital twins gradually increases over time, which would alter the situation that predictive, prescriptive, and autonomous digital twins are still in the infancy stage. On the other hand, technologies like IoT, cloud, and Wi-Fi have almost become the standard configuration of digital twin architectures, offering a firm basis for data storage and transmission. That also explains why most frameworks can be labeled with the monitoring function. However, it should be noted that the imaginary and recollection digital twins received little attention, consistent with [5,15]'s findings. Due to the irreversibility of living organism growth, it is necessary to investigate the two types in the future.

(4) Except for the documents not mentioning virtual representation, over half of the digital twins (19 use cases) chose the dashboard with graphical representation to show the digital twin. Surprisingly, an increasing number of the studies used advanced user interfaces: simulation (15 use cases), 3D visualization (6 use cases), and Virtual Reality (2 use cases), accounting for a considerable proportion. In particular, works with the approach of 3D visualization and Virtual Reality occurred at a later stage. The last two interaction methods make the digital twin applications more comprehensible and actionable. Farmer users then may operate and accept the applications more easily. At the same time, a series of issues await to be solved. For example, it is hard to use a 3D rendering model on a large scale, and inconsistencies will appear when the physical entity changes [37]; the application of Virtual Reality needs to take into account some limitations like high cost and simulation sickness [22].

5. Discussion

5.1. Research Progress of Digital Twins in Agriculture 2021–2023

According to the literature review, the influence of digital twins in agriculture has been expanding in recent years. Compared with the studies before 2021, the latest research progressed mainly from the following three aspects.

(1) Layers in the reference architecture of agricultural digital twins have been further developed. The above review indicates three main changes. First, most physical entities of interest previously were agricultural fields, farms, and landscapes [8], but currently, many are living organisms or living systems, such as crops, animals, perishable agri-food, and food supply chains. Some scholars pointed out that the unique features of those living objects should be weighed, e.g., [51]. Second, emerging technologies, like machine learning and Generative AI, were finding their roles in coupling physical entities with virtual ones. Third, compared with the dashboard in earlier studies, more and more digital twin frameworks leveraged simulation, 3D visualization, and Virtual Reality for virtual presentation, enhancing the ease of use.

(2) Studies expanded design perspectives, sub-fields, and benefits of agricultural digital twins. In terms of design perspective, more and more studies have started to design digital twin reference architectures based on a system and even the SoS level. Digital twins can play roles in agriculture from a broader perspective, such as the entire crop growth process, beer production line, and food supply chain from suppliers to retailers. Meanwhile, studies tried to apply their digital twin systems in the operational environment, and some of the digital twins, especially the system-level ones, have been implemented in the real context. However, most digital twins at the SoS level are still in the conceptual or experimental stage, calling for possible debugging and a better integration with all operational hardware/software. When it comes to the sub-fields, domains like the food supply chain and horticulture received increasing attention; studies brought the digital twin into forestry in which several open issues like collection of real-time data are worth noting [69]. The above twofold progress finally leads to the richer benefits of agricultural digital twins in relevant areas.

(3) Several new issues received attention instead of the pure concept. On the one hand, a considerable proportion of digital twin frameworks were not labeled as "conceptual" but "prototype" with richer functions, including prediction, prescription, and automation. That is, studies expect the digital twin to play a more significant role in agriculture. On the other hand, qualitative research has put forward some fresh topics, or rather concerns, such as possible threats, simulation sickness, and the high cost of agricultural digital twins. We can find that many of them could have a bearing on real-world implementation of digital twins in agriculture. That scholars consider the digital twin with a dispassionate attitude can not only benefit this technology but the agricultural industry.

5.2. Open Questions for Agricultural Digital Twins

Agriculture has unique characteristics, such as various living organisms, dynamic environmental factors, and quantity of smallholder farmers, making it harder to apply digital twins in related sectors compared to in other industries, like the manufacturing industry. Obviously, there is still a long way to go for the agricultural digital twins. Thus, it is imperative to shed light on RQ4 (What are the open questions for digital twins in agriculture?). To do so, this section lists some representative issues that need to be addressed urgently, which could give insights into future research.

5.2.1. Building Digital Twins Adaptable to Agriculture

As we mentioned, a long value chain exists in agriculture from the initial sowing to production, distribution, and finally to fork. In addition to the hierarchical structure integrating unit-level digital twins into the system, even SoS-level digital twins, the particular characteristics of each process should also be sufficiently considered. Some scholars have realized this. For example, Pylianidis et al. [8] summarized two main distinctive characteristics of agricultural digital twins. The first lies in the direct or indirect connection with living systems and perishable products. During the preharvest process, measures such as using ontologies to describe the crop in detail [51] and introducing a new method to enhance the coupling precision of the virtual leaf [23] were proposed. The second one is the spatiotemporal dimension of digital twins' operation. Taking the temporal dimension as an example, Pylianidis et al. [8] proposed that it may not be necessary to build high-frequency interactions initially between the physical entity and its virtual one because living organisms grow slowly. Thus, future studies should carefully consider the variety of plants or animals, the environment, and their interactions. For example, the current agricultural digital twins were applied in specific scenarios, but many studies did not explain if the operational environment can affect the digital twin's introduction to other settings or areas. Also, when constructing the digital twin from a company or whole value chain perspective, studies need to take more stakeholders, like suppliers and consumers, into account. Furthermore, due to the irreversibility of living organism growth, the imaginary, predictive, and recollection digital twins deserve more attention. Technologies like Generative AI, Virtual Reality, and blockchain could help.

The postharvest process also calls for an investigation. As we mentioned above, many agri-foods are perishable. The losses and waste from farm to fork happen a lot. Moreover, smallholder farmers often live in rural areas and are unaware of the changing market information. The digital twin offers an ideal solution to tackle this [39]. On the one hand, studies can design the digital twin of the product and its supply chain to figure out the key factors influencing losses and waste. As such, it can further diagnose and predict negative situations and intervene in them. On the other hand, connecting the preharvest process with the postharvest one matters. For example, sales prediction and even contact farming can help farmer users make wise decisions at the early production stage.

Finally, future studies should take note of uncontrolled environment agriculture (UEA, aka open-space agriculture). This study found that the current studies paid more attention to controlled settings where the organisms and their surroundings are more stable and manageable. There is no denying that digital twin applications built in such spheres make significant contributions, but equally, UEA is one of the dominant production methods until now, especially in rural areas. In terms of crop production, studies can further investigate crops like corn and processes, including soil management, fertilization, and multi-processes. For husbandry, research can pay attention to animals like sheep and chickens and processes, including growth management and disease prediction. Other domains, such as aquaculture and forestry, are also noteworthy.

5.2.2. Data Acquisition Issues

According to the review, we found that data acquisition is the fundamental key but also one of the biggest obstacles in constructing agricultural digital twins. Sufficient and accurate data can support more system-level or SoS-level digital twins. However, three major problems must be solved: input data, data sources, and data accuracy. The first one has been discussed to some extent in the above section. We suggest fully considering the characteristics of agricultural physical entities.

For data sources, previous studies obtained or mostly expected to obtain data from sensors. It should be noted that the agricultural industry involves various processes with multi-agents. Obviously, it takes work to coordinate their relations. If sensors cannot be mounted in one step or data cannot be transferred among the processes, the digital twin design from a broader level would face challenges. That also explains why many use cases were sorted as the prototype and/or unit-level digital twin. The lab environment is relatively closed, and not all the factors could be mentioned. Some studies can only test the twinning between the physical entity and its virtual one based on another physical entity's data. For example, limited by data, Spyrou et al. [32] had to analyze the pharmaceutical cannabis production digital twin with other crop data. Therefore, studies tended to combine different databases and/or simulate the digital twin by giving preset data, but that could raise questions about the data accuracy.

For data accuracy, as Moreira et al. [55] pointed out, the more progress we make in data acquisition, the greater the need to examine the data. Combining data from different sources requires calibration and validation in particular [61]. They compared sensor data with satellite data to ensure that sensor data were reliable. However, data in agriculture are complex and usually from diverse sources [66]. Sometimes, researchers can only match different datasets instead of two or more comparable datasets for the same object. For example, Shoji et al. [43] leveraged two datasets collected at different times with different methods and ranges. They aimed to map a longer postharvest process of imported fruits, but the consistency of the two datasets also needs to be tested.

5.2.3. The Possible Dark Side of Digital Twins in Agriculture

A digital twin must be reliable and secure [15,49,74]. However, technology is a double-edged sword, not excepting the digital twin. Although some scholars consider that the real-world implementation of agri-food digital twins could not be very soon [47], avoiding or mitigating the possible negative influences can prepare for unexpected news and fuel the application. In addition to the simulation sickness [22], the study identified the following issues.

First, digital twins require actual data from actors involved in the value chain, such as farmers, traders, retailers, and consumers, which could cause privacy issues. Raba et al. [66] found that farmers are reluctant to offer access to their data due to ownership and security, hindering the development of digital twins. Effective privacy protection technologies and policies are thus indispensable.

Second, as we mentioned above, the worry of data ownership is one of the possible reasons farmers hesitate to offer data. In the age of information, data are king. Farmers or other producers should have the right to obtain their data, but overall, developers are relatively well financed and have access to the whole database, which could easily lead to the digital twin privilege [47]. Thus, whether digital twins can increase the gap between rich and poor? How can we prevent the digital divide in advance? These questions are worth pondering.

Finally, agricultural digital twins are mainly based on three methodologies, including data-driven, physics-based, and agent-based models [62]. Generally, they can monitor, predict, and optimize the physical entity based on preset goals or rules. However, living organisms might not always grow alongside the established patterns. Possible situations that machines may not understand could also occur. In such conditions, will digital twins underreact or overreact? Are all the reactions applicable to every organism? Who should be responsible for the inadequate reaction? Is there any mechanism to recognize and block the intervention of digital twins?

5.2.4. The Acceptance of Farmer Users

The digital twin in agriculture is still in its infancy, no matter the academic research or practical use. This technology requires users to invest heavily [37], and farming is labor-intensive and time-consuming, making it hard for farmers to adopt new technologies [60]. Thus, persuading farmer users or other small and medium-sized practitioners to accept digital twins should be a focus.

As we know, the food production business has always been risky. Thus, showing producers that digital twins are a great help in capturing profit is important. On the one hand, cost reduction is necessary. For example, creating cheaper and more precise electronic sensors is still an open challenge [40]. Also, developers need to design new business models for agricultural digital twins, like the leasing system. On the other hand, studies need to provide more quantitative evidence that digital twins benefit agriculture.

Governments or other non-profit organizations (NPOs) should actively take responsibility. Food producers operating on a small scale seldom know the emerging technologies due to a lack of resources or education opportunities. In this case, we should figure out what governments or NPOs can do to help them better understand and leverage the digital twin. Therefore, future studies can explore the influences of measures like infrastructure construction, subsidies, finance inclusion, and training.

6. Conclusions

Technology has changed agriculture. In the Agriculture 4.0 era, farmers will run their businesses in a very different way, primarily thanks to advanced technologies like sensors, machines, information technology, and other developing but sophisticated technologies [86]. However, agriculture is different from industries like manufacturing and service industries. Characteristics like unpredictable changes in living organisms and the natural environment, marginal farming, and small-sized operations often slow down the development and adoption of technologies in this area. The same trend has occurred for digital twin technology until now. By creating a virtual representation of the physical entity, it assists users in monitoring, predicting, and optimizing the production process, which will transform the traditional operations of agribusinesses. However, the technology is still in the early stages. To elaborate on the current status and progress in agricultural digital twins can shed light on future studies.

Based on 70 documents published after a peer-review process or in the peer-reviewed SSCI/SCIE journals, this study introduced the studies on agricultural digital twins from overall trends, focused areas (including domains, processes, and topics), reference architectures, and open questions. The review found that digital twin technology is expanding its influence in agriculture. Scholars have begun to establish the digital twins from a broader level with more comprehensive functions. However, there is still a long way to go. For example, future studies should pay much attention to the characteristics of living organisms and their twinning with virtual entities; leveraging a broader perspective to design the digital twin is worth noticing in agriculture; governments need to take measures to prevent privacy issues and data privilege; more evidence should be given to prove digital twins profit a lot in agriculture. With digital twins, agriculture will step into a new level, which requires the cooperation of all stakeholders.

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