future internet

Article

Application Scenarios of Digital Twins for Smart Crop Farming through Cloud–Fog–Edge Infrastructure

Yogeswaranathan Kalyani [1,*], Liam Vorster [1], Rebecca Whetton [2] and Rem Collier [1,*]

[1] School of Computer Science, University College Dublin, D04 V1W8 Dublin, Ireland; liam.vorster@gmail.com
[2] School of Biosystems and Food Engineering, University College Dublin, D04 V1W8 Dublin, Ireland; rebecca.whetton@ucd.ie
* Correspondence: kalyani.yogeswaranathan@ucdconnect.ie (Y.K.); rem.collier@ucd.ie (R.C.)

Abstract: In the last decade, digital twin (DT) technology has received considerable attention across various domains, such as manufacturing, smart healthcare, and smart cities. The digital twin represents a digital representation of a physical entity, object, system, or process. Although it is relatively new in the agricultural domain, it has gained increasing attention recently. Recent reviews of DTs show that this technology has the potential to revolutionise agriculture management and activities. It can also provide numerous benefits to all agricultural stakeholders, including farmers, agronomists, researchers, and others, in terms of making decisions on various agricultural processes. In smart crop farming, DTs help simulate various farming tasks like irrigation, fertilisation, nutrient management, and pest control, as well as access real-time data and guide farmers through 'what-if' scenarios. By utilising the latest technologies, such as cloud–fog–edge computing, multi-agent systems, and the semantic web, farmers can access real-time data and analytics. This enables them to make accurate decisions about optimising their processes and improving efficiency. This paper presents a proposed architectural framework for DTs, exploring various potential application scenarios that integrate this architecture. It also analyses the benefits and challenges of implementing this technology in agricultural environments. Additionally, we investigate how cloud–fog–edge computing contributes to developing decentralised, real-time systems essential for effective management and monitoring in agriculture.

Keywords: digital twin; crop farming; smart agriculture; cloud–fog–edge computing; multi-agent systems

check for updates

Citation: Kalyani, Y.; Vorster, L.; Whetton, R.; Collier, R. Application Scenarios of Digital Twins for Smart Crop Farming through Cloud–Fog–Edge Infrastructure. *Future Internet* **2024**, *16*, 100. https://doi.org/10.3390/fi16030100

Received: 23 February 2024
Revised: 12 March 2024
Accepted: 14 March 2024
Published: 16 March 2024

1. Introduction

Agriculture, the primary source of the majority of the globe's food, is one of civilisation's most challenging issues. To match the growing population's demand for food, advancements in agricultural production need to be sustainable; with increasing environmental variability due to climate change and the unsustainable dependency on agrochemicals, this is an increasingly difficult task. Technology advancement and increasing availability of low-cost sensors have led to a rise in the popularity of precision agriculture and smart farming to address the food production concerns [1]. Precision agriculture and innovative farming technologies enable farmers to be better informed and more adaptive in their response to changing weather conditions. Furthermore, the increased data help farmers to move away from traditional approaches of broadcasting agrochemicals towards target applications, which has both financial and environmental benefits.

The latest technologies, including sensors, computing edge devices, monitoring devices, smart agricultural equipment, and cloud services, are essential for enabling smart agriculture [2], precision agriculture, and Agriculture 4.0/5.0 [3,4]. These technologies have enabled the rapid adoption of advanced techniques in agriculture, such as cloud–fog–edge computing [2], digital twin [5], the Internet of Things (IoT) [6], big data analytics [7], machine learning [8], augmented reality [9], and robotics [10]. By utilising these technologies, farmers can improve sustainability, enhance productivity, and optimise resource utilisation. As these technologies continue to develop and become more accessible, we can expect to see more significant advancements in smart agriculture in the future.

Digital twin is an evolving technology that is gaining more attention in all domains. DT can be defined as a digital equivalent of a real-life object that mirrors its behaviour and states over its lifetime in a virtual space [11]. Although there are a number of studies available in other domains using the concept of a DT, it is still in the early stages in agriculture [5]. In recent years, agriculture has also received a lot of interest; development and implementation are still in progress as stakeholders and researchers work to find sustainable and efficient methods to produce food while also reducing the impact on the environment.

Farming can be generally categorised into two types: Open Environment Agriculture (OEA) and Closed Environment Agriculture (CEA). The implementation of DT in CEA is relatively easier because of the controlled nature of environmental factors. However, implementing DT in OEA is challenging because it involves unpredictable natural weather conditions and various other external factors. While a significant amount of research focuses on CEA, with studies exploring its application in greenhouse [12], aquaponics [13], vertical farming [14], hydroponics [15], studies on OEA are comparatively fewer. DT in agriculture is an emerging topic that has the potential to bring about significant change. Since a few studies are available for OEA, it is clear that there is a need for customised DT frameworks specifically for OEA. This gap has motivated us to propose architecture and application scenarios for open-environment crop farming. The detailed related work on DT for agriculture is discussed in Section 3.

This research introduces a novel architecture for a DT by integrating multi-agent systems and cloud–fog–edge computing. This is designed to rapidly provide necessary decision-making information to farmers for "what-ifs" scenarios. It also directs farmers in critical areas and offers a dynamic list of prioritised actions that adapt to evolving environmental conditions. Moreover, the proposed architecture has the capability to automate certain farm tasks based on farmer inputs. Therefore, it enhances overall farm productivity and effectively manages various tasks. Additionally, the paper explores a few detailed use cases, demonstrating the practical application of DT technology through integrated architecture in agricultural environments.

The remainder of this work is structured as follows: In Section 2 we describe smart crop farming (Section 2.1), digital twin technology (Section 2.2), and cloud–fog–edge computing (Section 2.3) as the background of this work. Section 3 discusses related works on Digital Twins in the agricultural domain. A high-level architecture for the proposed DT agricultural use cases is presented in Section 4. Section 5 explores possible application scenarios with digital twins, consisting of the overall scenario for agriculture (Section 5.1) and then describing specific scenarios, such as irrigation systems in Section 5.2 early alerts on fields in Section 5.3, nutrient management recommendations in Section 5.4, and nutrient deficiency risk identification in Section 5.5. Finally, Section 6 concludes the discussion and discusses future work.

2. Background

2.1. Smart Crop Farming

Agriculture plays a crucial role in today's world, as it is essential for feeding the global population. With a growing global population and limited resources [16], it is crucial to find innovative solutions to maximise crop yield and ensure food security. One such solution is the application of smart agriculture techniques, which utilise advanced technologies such as satellite imaging and remote sensing, drones and Unmanned Aerial Vehicles (UAVs), artificial intelligence, the Internet of Things (IoT), and robotics. Smart agriculture, often referred to as precision farming, digital farming, or agriculture 5.0 [4], aims to optimise agricultural practices by utilising the power of data and technology. Smart agriculture, also known as precision farming or digital farming [17] or agriculture 5.0 [4], aims to optimise the farming process by increasing accuracy and customisation for specific fields or crops. Using these technologies, farmers can collect real-time data on soil moisture, temperature, nutrient levels, and pest infestations. These data can then be analysed and used to make data-driven decisions about irrigation, fertiliser application, pest control, and crop management. By integrating smart technologies into agriculture, farmers can not only increase crop yields but also reduce resource wastage.

Crop farming is generally complex and relies heavily on various factors such as weather conditions, soil quality, irrigation management, fertiliser and nutrient availability, and pest control. In the past, farmers had to rely on traditional methods and intuition to make informed decisions [18]. However, with the introduction of smart agriculture or smart farming, farmers now have access to real-time data and accurate weather forecasts compared to the past. This helps them make timely decisions regarding when to plant, irrigate, or harvest their crops to optimise yield. To address this challenge, farming now demands a decision support system and monitoring system [19]. This is where the IoT plays a crucial role. The IoT refers to the connection of physical objects, devices, and sensors through the internet to gather data for decision-making [20]. By implementing IoT technology in agriculture, farmers can collect data from various sensors and devices placed throughout their fields. This data can then be analysed using artificial intelligence algorithms to provide insights and recommendations for improving crop production. Other technologies, such as machine learning, blockchain, and robotics, can also be integrated into smart agriculture systems to automate tasks, reduce labour costs, and improve efficiency. Digital twin technology in agriculture is another emerging concept that holds great potential in smart agriculture. Overall, smart crop farming is transforming traditional methods of farming, bringing about a new era of efficiency and productivity in the agricultural sector.

2.2. Digital Twin

In recent years, the DT concept has garnered global attention. It involves creating a virtual or digital replica of a physical object, such as machinery, buildings, farms, fields, plants or even human beings, using real-time data from these physical entities. This approach allows for comprehensive analysis, simulation, and optimisation. The term digital twin, introduced by Grieves in a 2003 presentation and later elaborated in a white paper [21], has provided the foundation for its development across various domains. Digital models are created by collecting real-time data from IoT solutions, such as sensors and other sources. DT systems are different from other systems as they not only simulate predicted futures but also provide real-time insights. Unlike simulations [22], DTs use real-time data and can provide quick and valuable information by incorporating the latest available data.

Although DT technology originated in manufacturing [23], its application has broadened to sectors such as healthcare [24], energy [25], urban planning [26], and recently in agriculture [27]. In agriculture, digital twins have revolutionised practices by simulating farming cycles such as soil conditions, weather patterns, crop growth, and pest infestations and utilising real-time data for decision-making. This approach allows for customised recommendations, optimising crop yields, efficient resource use, and minimising environmental impacts.

Digital twins improve precision farming by creating accurate digital replicas of farms, enabling remote monitoring and management. Farmers can customise irrigation and fertilisation plans and accurately predict harvesting times. As advanced predictive tools, these models help manage risks like crop diseases and pest infestations effectively. Integrating artificial intelligence and machine learning [28] further provides advanced analytics and predictive insights essential for sustainable food production and climate change adaptation.

Even though introducing DTs in agriculture offers many benefits, adopting this technology faces challenges [29], including the need for significant initial investment, a robust technological infrastructure, and concerns regarding data privacy. Despite these limitations, the future of DTs in agriculture and beyond looks promising, with potential advancements such as enhanced integration with advanced technologies.

2.3. Cloud–Fog–Edge Computing

Cloud–fog–edge computing is a paradigm that combines the power of cloud computing, fog computing, and edge computing to create a distributed and collaborative computing platform. At its core, cloud–fog–edge aims to optimise the processing and storage of data by leveraging the strengths of each computing model. Utilising cloud computing, this architecture can benefit from its vast resources and scalability for handling large-scale data processing and storage [30]. Fog computing, on the other hand, brings the computational power closer to the data source, reducing latency and improving real-time processing capabilities [31]. Edge computing enables processing and storage to be performed at or near the edge devices themselves, reducing the need for data transmission and thus improving efficiency. This combination of cloud, fog, and edge computing addresses the limitations and challenges of traditional centralised computing models.

As the agriculture domain evolves with the integration of cloud, fog, and edge computing, a powerful architecture emerges that significantly impacts farming practices. Edge computing, situated closer to on-field devices, ensures fast data processing and minimal latency, which is essential for real-time decision-making [32]. However, fog computing plays a pivotal role in this integration, not only seamlessly connecting with edge devices but also conducting intelligent analysis [33,34]. The unique capability of fog computing to extend its reach to both the edge and the cloud makes it an indispensable component of agricultural systems. The introduction of mobile fog zones, actively gathering data from the fields, and static fog zones, providing localised storage and computing capabilities for immediate data analysis, marks a crucial transformation [35]. This cloud–fog–edge combination architecture not only optimises data processing and decision support at the field level but also leverages cloud resources for comprehensive analysis. The importance of fog computing in agriculture is underscored by its role in bridging the gap between on-field operations and broader cloud-based insights, thereby enhancing the efficiency, scalability, and adaptability of agricultural practices.

3. Related Work

Recent reviews show that interest in DTs in agriculture has notably increased in the last few years. For instance, the authors of [27] presented an extensive literature survey on DTs in agriculture, establishing a foundational understanding of the topic. The authors of [36] examined the application of the DT paradigm in assessing soil quality, highlighting the technology's potential to revolutionise traditional practices. Further, Ref. [13] introduced a pioneering case study on urban farming technology. This study explored how a cyber-physical aquaponics system, augmented with a DT and machine learning, could gain adaptive capabilities, showcasing the practical implementation and benefits of DTs in enhancing agricultural systems.

Verdouw et al. [11] analysed how DTs could advance smart farming. The authors defined the concept of a DT, developed a typology of different types of DTs, and proposed a conceptual framework for their design and implementation. The authors mentioned that DTs in agriculture include six distinct types: imaginary, monitoring, predictive, autonomous, and recollection DTs, each serving different control purposes. The authors also proposed a framework and applied and validated it in five smart farming use cases in the European IoF2020 project, covering arable farming, dairy farming, greenhouse horticulture, organic vegetable farming, and livestock farming. The case studies have offered valuable insights into how DTs can improve and optimise smart farming systems.

In 2021, Pylianidis et al. [27] published a literature review on digital twins in agriculture from 2017 to 2020. The authors identified 28 use cases and compared them with other domains' use cases. The authors compared reported benefits, service categories, and technology readiness levels to assess the level of digital twin adoption in agriculture. The authors also proposed a roadmap inspired by other domains of DT applications. This paper concluded by identifying distinctive characteristics of agricultural DTs. However, this paper did not provide specific examples of implemented DT applications in agriculture or the latest advancements in this field. It also did not cover potential benefits in detail or the latest advancements in DT applications in agriculture.

Nasirahmadi et al. [5] presented a general framework of DTs in soil irrigation, robotics, farm machinery, and food post-harvest processing in the agricultural field. The authors emphasised the need to develop DT systems further in the agricultural context. These systems should be able to monitor, record, and analyse data to predict and prescribe the best decision for digital farming management. Also, the authors identified the need for further research and development in applying DT concepts in agriculture, particularly in addressing practical challenges, integrating advanced technologies, and developing robust DT models for different aspects of agricultural operations.

Few other studies are available that apply the concepts of DTs to smart agriculture. For example, Ref. [37] proposed a DTs-based smart agriculture framework utilising LoRaWAN for sensor networks in farm fields and the intelligent processing of aerial imagery to detect plant diseases and nutrient deficiencies. The authors of [13] have proposed a framework for a decision support system to coordinate decentralised urban agricultural production units. The authors of [38] discussed the principles of developing a multi-agent DT of plants using broccoli as an example.

The results of the reviews clearly show that the concept of DTs in agriculture is still in its early stages and has not been fully explored in research. Although the agricultural sector presents numerous opportunities for the application of DT technology, its development and implementation are still in progress. Therefore, this paper proposes a set of DT use cases designed for the agricultural domain. The aim is to bridge the current research gap and contribute to sustainable agriculture and enhanced production goals. This paper focuses on applying the innovative DT concept to real-world scenarios in smart agriculture. Our goal is to tackle key challenges in this field, with the promise of revolutionising efficiency and yield through this approach.

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

Figure 1 illustrates the proposed architecture of a DT system for smart agriculture that integrates cloud, fog, and edge computing layers and multi-agent systems. Farmers or users can access a DT system through a farm management GUI (Graphical User Interface). The overall architecture consists of three layers: Cloud, Fog, and Edge.

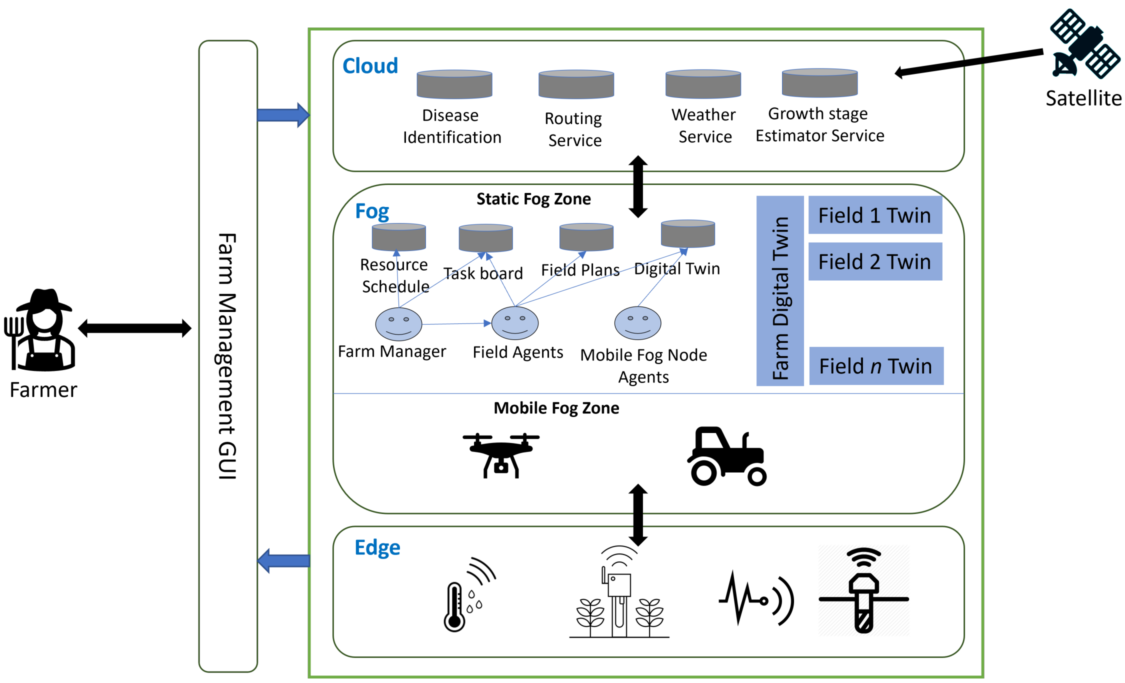

Figure 1. Proposed Architecture for Digital Twins in Smart Agriculture.

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

The Fog layer consists of two sub-zones: the Static Fog Zone and the Mobile Fog Zone. In a smart or precision farming setup, an array of sensors and actuators are employed, along with machinery like harvesters, tractors, and innovative devices such as drones and agricultural robots. These devices function as mobile fog nodes, gathering data directly from the fields. Located at the field level, the Static Fog Zone hosts agents, microservices, and digital twins, providing localised data storage and computing capabilities for immediate analysis of farm data. The mobile fog nodes serve to extend the reach of the Fog network, ensuring data collection and processing capabilities in parts of the farm that may have intermittent or no internet access. Furthermore, the Fog layer incorporates a collection of microservices, which facilitate access to both internal APIs for farm data retrieval and third-party APIs (Application Programming Interfaces) for extended functionality. It also houses various agents, such as the Farm Manager and Field Agents, who are tasked with resource scheduling, task management, and the execution of field plans. These components function seamlessly within both the static and mobile zones of the Fog layer.

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

Additionally, the overall architecture incorporates MAMS (Multi-agent Micro-services) [39] as illustrated in Figure 2. In this setup, microservices are tasked with ongoing activities like weather monitoring and are engaged in the continuous processing of data. The system's flexibility allows seamless transitions between different data sources, like switching from one weather station to another, by simply re-configuring the appropriate microservice. This adaptability level is a fundamental feature of DT technology and is further enhanced by the integrated multi-agent system. In this interconnected environment, actions in one field can influence outcomes in another. The DT plays a crucial role in fine-tuning these decisions, utilising data-centric simulations. At the core of this architecture is the utilisation of established agricultural guidelines, such as the RB209 recommendations, providing a solid foundation. These guidelines are not just followed; they are dynamically adapted to suit the real-time conditions of the farm, ensuring the advice provided is both reliable and contextually relevant.

On the other hand, agents play a crucial role in the DT framework, particularly in decision-making, task allocation, and resource management. These intelligent agents utilise the data gathered by microservices to make not only decisions but also recommendations. A comprehensive knowledge graph is built by a variety of microservices, such as those collecting weather data, nutrient recommendations, and decision-making services. This interconnected data representation enables agents to coordinate system activities effectively. This ensures the maintenance of the most accurate model of the field's state. The agents are focused on developing an efficient plan for the field. Although this plan is not a built-in feature of the DT, it is significantly influenced by the data collected and analysis from the DT. This field plan directly impacts nutrient levels, which in turn affects the growth stages of the crops. Efficient management of the DT, coupled with the use of intelligent agents for decision support, enables us to recommend strategies that maintain optimal field conditions, enhancing both the productivity and efficiency of agricultural practices. The agents can also analyse patterns, predict outcomes, and allocate tasks efficiently across the farming operation. Their capabilities include assessing the best planting strategies, optimising irrigation schedules, and managing resource allocation to maximise yield and efficiency.

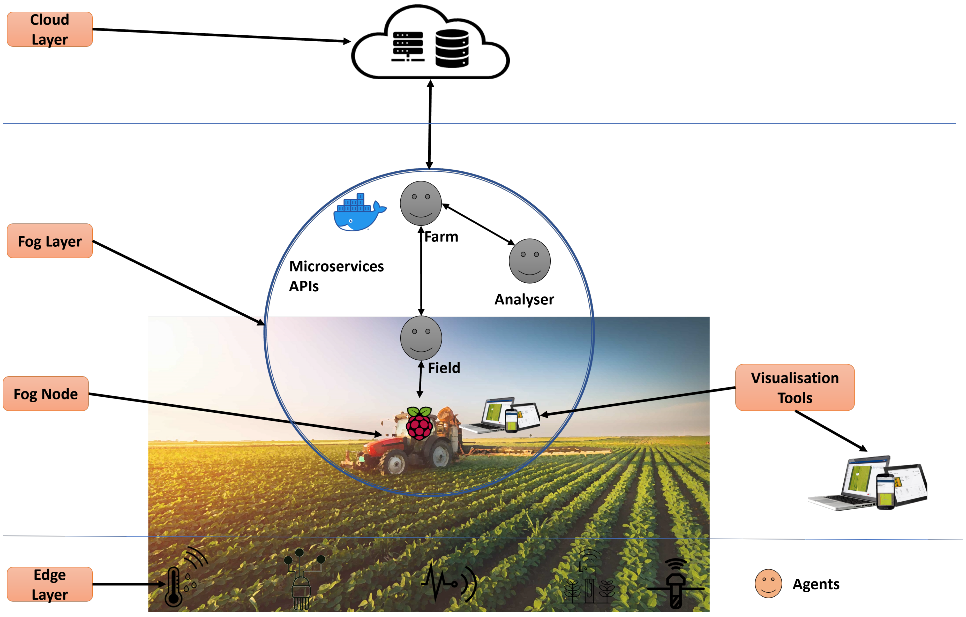

Figure 2. Cloud–Fog–Edge and MAMS Overview.

Overall, the proposed architecture depicted in Figure 2 enables farmers to utilise a DT that integrates cloud computing, fog computing, and edge computing, thereby simplifying and improving farm management. This approach significantly enhances farm management and decision-making through a comprehensive, multi-layered computational framework. The incorporation of agents in this architecture allows for autonomous data collection and processing, ensuring timely and accurate information. Microservices, meanwhile, offer modular and scalable solutions, facilitating the flexible integration of various farm data sources and services. The combined use of cloud, fog, and edge computing layers ensures efficient data processing: cloud computing handles complex, non-time-sensitive tasks; fog computing provides localised data analysis; and edge computing enables real-time data capture directly from farm devices. Collectively, these technologies form a digital replica of the farm that includes all important factors, thereby streamlining decision-making. In this way, the proposed architecture offers numerous advantages in overall farming processes compared to the existing agricultural systems.

5. Possible Application Scenarios with Digital Twin

In the labour-intensive field of agriculture, many interrelated and variable factors play a role in daily farming decisions. Despite being well-planned with expertise, unforeseen circumstances often cause plans to be changed or abandoned in cases such as unexpected rainfalls or the emergence of crop diseases. In these circumstances, an adaptive approach, a fast decision, and good organisation are essential to maintain efficiency and prevent yield losses (subsequently financial losses) and environmental damage. This section discusses example use cases using DTs.

5.1. Overall Scenario of Digital Twin in Agriculture

The proposed DT model of agriculture includes a digital representation of farms, fields and other related factors. This complex model dynamically integrates various data sources to replicate the current state of the farm. This model is also continuously updated with real-time data, allowing it to reflect current conditions and predict future states accurately.

For instance, if we consider a farm with n fields, the DT model would have the exact representation with details such as:

- Farm: Farm ID, Farm Name, Number of Fields, Field IDs.
- Field: Field ID, Farm ID, Field Name, Crop Info, Soil Info, Historical Information such as Last Cropping Date.
- Zone: Zone ID, Zone Name, Field ID, Farm ID, Weather Data.

As illustrated in Figure 3, digital twins assist in decision-making and predictions based on historical and real-time data analysis and provide recommendations and suggestions to farmers and other stakeholders.

Digital twins can be applied to various aspects of agriculture in order to help farmers, including:

- Real-time Monitoring and Prediction [5]: DTs can monitor crop health and growth in real-time and predict future outcomes based on data such as weather patterns, soil moisture, and nutrient levels. This information can help farmers make informed decisions about irrigation, fertilisation, and other factors that impact crop growth.
- Enhanced Productivity and Efficiency: By simulating various scenarios, farmers can identify the most efficient use of resources, such as water and fertilisers, and optimise crop yields [5,12]. As new data are collected and analysed continuously, farmers can continuously refine their practices, adapting to changing conditions and incorporating the latest insights for ongoing improvements in productivity and efficiency.
- Resource optimisation and management: DTs can optimise farmers' use of resources like water, fertilisers, and pesticides by providing real-time data on their application and effectiveness. It also helps in task scheduling and management of farm equipment, including tractors, harvesters, and other agricultural machinery. This can help farmers reduce waste and improve efficiency.
- Quality control: It can monitor crop quality and identify potential issues, such as pests or diseases, before they become significant problems. This can help farmers take proactive measures to protect their crops and maintain high-quality yields.
- Collaboration: DTs can facilitate collaboration among farmers, researchers, agronomists, and other stakeholders, allowing them to share real-time data and insights. This can accelerate the development of new techniques and technologies in smart crop farming.
- Data-Driven Decision-Making: DTs offer farmers a comprehensive perspective of their agricultural operations. This enables data-driven decision-making, as farmers can analyse soil conditions, weather patterns, and crop health data to make informed choices toward improving yields. Continuous data collection and analysis enable better management of agricultural processes, leading to more informed decisions [5].

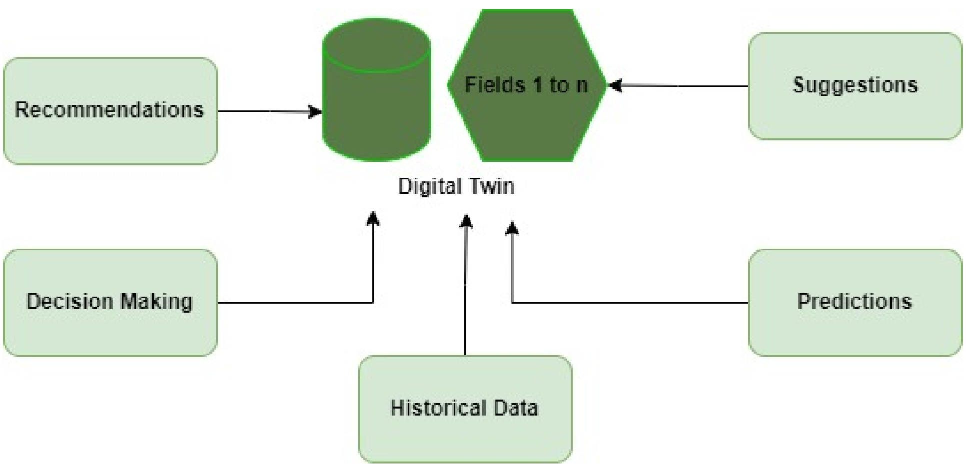

Figure 3. Digital Twin for Agriculture.

The implementation of a DT in agriculture is a powerful step towards more efficient and sustainable practices. This approach offers a holistic overview of the farm, enabling farmers to optimise processes throughout the entire agricultural cycle, from planting to harvesting. The DT also has features for predicting the future and a comprehensive understanding of farm processes. Farmers can more efficiently use resources like water, fertilisers, and pesticides. As a result, this reduces waste and operational costs and addresses the specific needs of crops at different growth stage levels at the right time. These all help in maximise yields.

Integrating data from diverse sources and analysing them are significant features of DT. This integration includes real-time data from IoT devices distributed across the farm, which monitor key factors such as soil moisture and nutrient levels. Weather patterns are important in making decisions about farming activities. The data coming from local weather stations can offer valuable insights in terms of how the weather patterns could change. Additionally, the DT utilises high-resolution satellite imagery to monitor larger-scale changes in crop health and environmental conditions. The DT improves its predictive accuracy by accessing agricultural databases to collect data on crop varieties, pest/disease patterns, and historical data. This can result in guiding farmers towards more informed decision-making in modern agriculture.

The DT not only simulates and predicts the outcomes of different farming strategies under varying environmental conditions but also continuously updates its model to reflect real-time changes on the farm. This dynamic model ensures that the virtual farm environment is always in sync with the actual farm, allowing farmers to visualise the consequences of their actions before implementing them. By acting as a decision-support tool, the DT enables farmers to efficiently manage risks, such as pest infestations or disease outbreaks, and test different scenarios, including best and worst-case situations. Ultimately, this approach supports sustainable and environmentally friendly farming practices, empowering farmers with the tools needed for success in the ever-evolving world of agriculture.

In the following section, we will explore a few use cases that demonstrate the potential of DTs in agriculture: irrigation systems and early disease detection. Specifically, we will compare the processes for these use cases with and without DT technology. Figures 4 and 5 illustrate these processes and highlight the benefits of using a DT.

It is worth noting that with DTs, it is necessary to consider all related factors before making a decision instead of only considering a single factor. This feature enables farmers to make more accurate decisions that consider the potential future effects of the decision rather than simply deciding whether to irrigate or manually identify diseases. This is one of the key advantages of DTs compared to other modern digital systems.

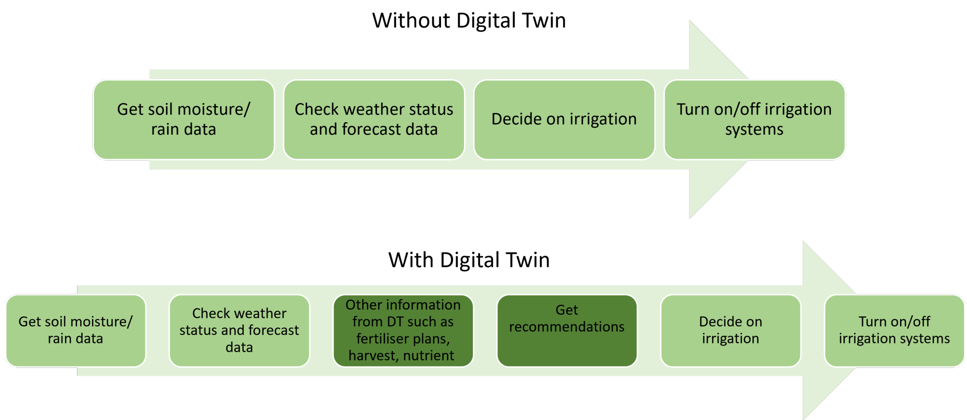

Figure 4. Irrigation Systems.

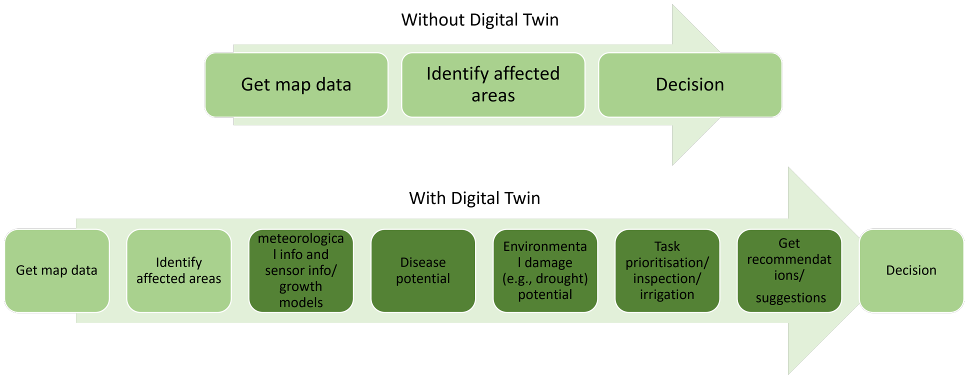

Figure 5. Early Alters on Fields.

5.2. Scenario 1: Irrigation Systems

Agricultural irrigation systems are frequently closed systems, which require the farmer to turn the irrigation system on or off. More advanced systems are available on the market, which utilise either soil moisture sensors [40] or rainfall sensors [41] to automate irrigation and reduce water usage. The sensors for automated irrigation systems are typically expensive. As technology advances, progressively more straightforward, low-cost sensors capable of sensing soil moisture and rainfall are entering the market. Connecting these simple sensors to nodes would create an affordable irrigation management system. This would lower the cost barrier and allow greater access to precision technologies, particularly for smaller farms [40].

A DT for an irrigation system in agriculture is a digital replica of the physical irrigation system used in the field. It is created by collecting data from sensors and other sources such as weather forecasts, soil moisture sensors, and crop growth models. Using this data, the DT replicates the functioning of the irrigation setup and the behaviour of the crops under irrigation. This enables farmers and other stakeholders to monitor system performance, optimise irrigation schedules, and make better decisions to maximise crop yield while minimising water usage. For example, the DT can help farmers decide when and how much water to apply to their crops based on weather conditions, soil moisture levels, and other factors (harvest date, fertiliser plans). It can also help farmers identify potential issues with the irrigation system, such as leaks or malfunctions, and take required action before they impact crop yield.

Farmers who do not have access to DT technology must rely on traditional methods such as visual inspection and manual measurement to make irrigation decisions. These methods are often based on intuition and experience rather than hard data, which could lead to inefficient and suboptimal irrigation practices. While there are modern irrigation systems that use technologies such as soil moisture sensors and temperature gauges to inform decision-making [42], these systems may not take into account other important factors such as crop growth stage, nutrient levels, and fertiliser use. Digital twin technology, on the other hand, can integrate and analyse a wide range of data points, making it a more advanced tool for decision-making in agriculture. A DT for an irrigation system of crop fields can provide farmers with a valuable tool to improve their irrigation practices and ultimately achieve more sustainable and efficient crop production.

Additionally, the fog processing feature outlined in this paper's architecture, as illustrated in Figure 1, allows for the utilisation of weather forecasts in conjunction with simple sensor data. This integration helps to reduce water usage further. Reducing water consumption is crucial for countries experiencing water scarcity. Due to climate change-induced water shortages, agricultural security concerns are increasing [43]. Therefore, utilising DT in irrigation systems presents an effective solution for this issue.

5.3. Scenario 2: Early Alerts on Fields

Vegetation indexes used in earth observations are related to crop stress, such as drought or disease [44,45]. The field management system in the outlined architecture would prioritise an inspection made in a specific area in response to earth observations processed through the cloud. This guidance-based approach would rapidly reduce the time spent inspecting the field for stress symptoms, increasing efficiency and helping maintain crop health. This is illustrated in Figure 6, where the traditional approach of crop inspection requires walking through each field as highlighted on the left image with red lines; the guidance-based system reduces this need and can direct a farmer straight to the areas of risk. Whilst in the field, any map-based information could be updated through the static fog, and the farmer could record a diagnostic for the stress (e.g., the presence of a disease). In addition, whilst in areas of poor connectivity, sensors would benefit from the presence of a passing smartphone to create an ad-hoc connection to upload data. At the point of updating the system to diagnose a crop disease, the architecture will be able to respond to this new information, check the weather forecast, and, if weather conditions are favourable could prioritise new actions of fungicide applications (part of the recommendation system of the architecture).

Additionally, the system could automate the shutoff of irrigation of the field/neighbouring fields of the same crop. This automation will (1) help reduce the spread of disease from water droplets and (2) provide the most time for the area to dry, which is necessary for fungicide applications. The dynamic nature of the architecture will provide the best outcome for a rapid response. In this scenario, the system minimises the time spent by the farmer inspecting fields, collecting relevant information (i.e., weather forecast), deciding on the best course of action and allowing more time for the farmer to respond to the crop disease threat, preventing potential yield reduction from crop disease spread. Without the system, most of the day could have been spent inspecting each field for symptoms of stress.

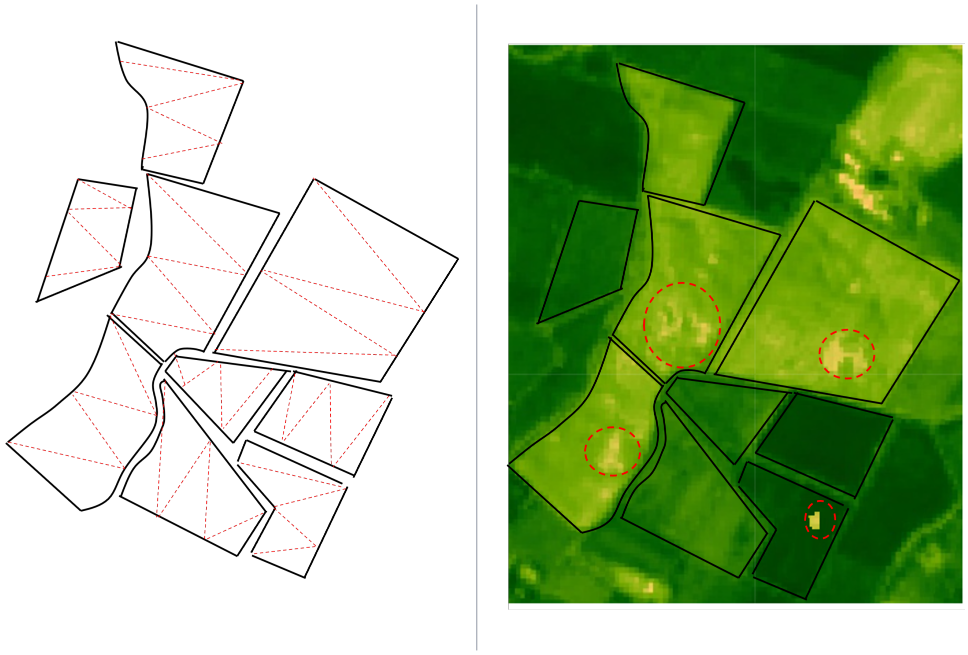

Figure 6. Crop Inspection Traditional Approach (**left**) vs. Modern Approach (**right**).

When there is a deviation from the farm management plan, the DT field feature will be able to simulate the impacts of the change and provide advice on future management decisions. If an event occurs in a field or management deviates from the management plan, the digital twin field will be able to simulate the impacts of the changes and advise alternative management decisions. For example, if the drilling of a field is delayed due to adverse weather events, the DT will recommend increasing the seed rate, helping to negate any reduced tillering. Furthermore, the DT model will be able to apply these variations, along with growth modelling and external data such as weather forecasting, to adapt the expected timing of future management actions, e.g., nitrogen applications. The DT will be able to suggest amendments to agrochemical applications in response to events occurring in the field/farm while also helping to automate certain processes. In addition to this, if yield reduction is predicted for a field in the DT, the system may suggest reducing future nitrogen applications in that field, which will help improve nitrogen use efficiency, reduce environmental damage, and maximise profits.

5.4. Scenario 3: Nutrient Management Recommendations

Nutrient management is crucial in crop farming for several reasons. It ensures the optimal growth of crops by providing them with the right balance of nutrients [46]. Effective nutrient management not only boosts crop yield [47] and quality but also minimises the environmental impact by reducing fertiliser overuse and runoff, which can lead to soil degradation and water pollution [46].

Various factors are considered in nutrient management for crops, including soil conditions, crop nutrient requirements, deficiency symptoms, previous crop information, and environmental conditions [48]. Conventional smart agriculture [49] employs technologies such as IoT sensors, drones, and satellite imagery to gather data for informed fertiliser application, improving crop growth, and minimising waste. However, these systems face challenges in terms of connectivity and internet access in remote agricultural areas, impacting the real-time monitoring capabilities of these technologies. Another problem is scalability when new services need to be introduced to the systems.

Generally, the conventional smart agriculture method of nutrient application involves uniform practices across fields. In contrast, the proposed architecture customises nutrient guidance based on the unique needs of each field or zone level, as identified through real-time data processing. This is because the DT supports farm level, field level, and zone level granularity. The adaptability of the DT is evident in its responsiveness to dynamic environmental factors. In instances of adverse weather conditions or changes in soil composition, the system can promptly adjust nutrient recommendations to accommodate the evolving needs of the crops. This agility ensures that nutrient applications are modified with the current state of the field, maximising the effectiveness of the entire nutrient management process.

Additionally, the system facilitates seamless communication between various stakeholders involved in nutrient management. Farmers receive clear and actionable recommendations through user-friendly interfaces, improving their ability to implement precise nutrient applications. The recommendation system also integrates with other components of the agricultural architecture, such as weather forecasting, to provide comprehensive insights for decision-making. Another key feature of the nutrient management recommendation system using DT architecture is its continuous learning capability. Over time, the system refines its recommendations based on historical data, crop responses, and evolving soil conditions. This iterative process ensures that nutrient management strategies are continually optimised, leading to improved crop health and overall agricultural productivity.

Furthermore, integrating cloud, fog, edge computing, agents, and microservices transforms nutrient management to the next level. The fog layer instantly analyses real-time data collected by edge devices, overcoming connectivity limitations. Microservices provide flexible and scalable solutions, while the cloud layer enhances computational capabilities with machine learning. Autonomous agents streamline decision-making, making nutrient management more efficient and reducing the need for continuous human intervention. The whole approach of the DT architecture ensures a seamless and optimised nutrient management process in agriculture.

5.5. Scenario 4: Nutrient Deficiency Risk Identification

Nutrient deficiency risk identification is a traditionally onerous task in which farmers may heavily rely on experience and generational knowledge [4]. Identifying a nutrient deficiency is often done through visual inspection of crops, as nutrient deficiencies result in symptoms appearing on the plant [4]. If visual symptoms are missed, a farmer may only realise the potential for nutrient deficiencies when observing a reduced yield and/or poor plant quality. Problematic crops may prompt a soil test, which serves as the most accurate representation of soil pH and key nutrient levels. However, when a deficiency has manifested, it is often too late to treat it effectively. Therefore, due to the variable nutrient requirements of different crops, farmers often utilise strategies such as crop rotation and intercropping to maintain a balanced soil nutrient profile.

Conventional smart agriculture techniques have been developed to identify nutrient deficiencies in soils and crops. This is primarily achieved through satellite imagery [50], machine learning [51], and IoT sensors [52]. Some techniques relying on imagery may prove insufficient in some scenarios, as treating nutrient deficiencies can be ineffective by the time it is visually present. IoT sensor solutions facilitate rapid data collection, thereby enhancing decision-making efficiency [52]. The adoption of IoT sensors has proven to improve the quantity and quality of yield [52].

An implemented DT architecture offers a basis to integrate heterogeneous, dynamic, and disparate data sources into a homogenous system. This uniform system can underpin mechanisms that proactively monitor for coinciding and compounding risk factors for key nutrients, such as a field of a particular soil being waterlogged during the winter months. The result of this could be a notification to a farmer that a field is exposed to a greater risk of certain nutrient deficiencies. The use of edge services, as in the proposed DT, ensures the integration of real-time data into risk identification processes. The DT transforms the approach to nutrient deficiency, as the seamless integration of interoperable data enables holistic techniques for risk identification in real-time. Furthermore, this strategy is enhanced by being employed by a multi-agent system. The distributed nature of agents allows for simultaneous monitoring of multiple fields in parallel. The autonomous aspect of agents ensures a proactive risk identification process. This transitions a farm's nutrient deficiency management strategy from being reactive to preventative, as actions can be taken to mitigate risk as the dynamic data is updated in the DT.

6. Discussion and Future Work

In conclusion, the DT concept is a powerful innovation with promising applications in agriculture, particularly when integrated with other cutting-edge technologies such as multi-agent systems (MAS), cloud–fog–edge computing, and microservices. The rapid advancement in sensing, communication, and computing technologies has sped up the development of DT models. These models replicate real-world conditions with real-time data, improving farm operations and allowing for better planning by offering suggestions for different 'what-if' scenarios. This paper introduces a DT architecture and explains its components. While this architecture holds potential for numerous applications in agriculture, our current focus is on practical implementations, such as developing irrigation systems for crops, early disease detection, nutrient management recommendations, and identifying nutrient deficiency risks. The proposed structure uses agents and microservices to create and develop a cloud–fog–edge infrastructure, establishing the foundation for promising research in sustainable smart crop farming.

The possible expected challenge would be accessing all the required data in the field. This data can be collected from sensors and third-party APIs for weather and other data. Implementing DT in agriculture demands solid technological infrastructure, including sensors, IoT devices, and cloud–fog–edge infrastructure. In addition, to apply this in the real world, the initial cost to install the required devices and technologies must be higher if it is not a smart farm. However, the proposed architecture is most suitable for smart agriculture. Thus, most smart farms already use smart agricultural devices such as drones, sprayers, sensors, etc. Regarding this architecture, cloud hosting and accessing accurate data from third-party APIs such as satellite data may also be expensive. Agriculture is generally a highly complex domain influenced by various unpredictable variables such as weather conditions and patterns, soil conditions, and other environmental factors. Although we get these predicted data from sensors and weather stations, it might still be unreliable. Nowadays, most farms are already using some level of technology and devices. Therefore, integrating with the existing systems in DT may be challenging. Implementing DTs involves collecting and analysing vast amounts of data, raising concerns about data privacy, ownership, and security. In addition to this, well-written documents and manuals should be prepared for use by agricultural stakeholders.

From our perspective, the proposed architecture can be validated in several ways. For instance, it can be simulated with historical data, applied to a small-scale farm, and seen in the field without applying a digital twin. Additionally, it is possible to do qualitative testing based on farmers' feedback based on the user experience. Another possible way would be to check how the DT reacts to the real-time data. However, further research is needed to analyse the real challenges and benefits of the proposed architecture.

We are in the process of implementing the proposed use cases. For our future work, we plan to concentrate on several areas, investigating the design constraints involved in implementing DTs with cloud–fog–edge computing and identifying the challenges and potential solutions in the domain of agricultural DTs. In addition to this, we are also planning to propose a framework to implement a DT for agriculture domain. The future work will be also focusing on how these DT can be evaluated in the real world.

Author Contributions: Conceptualization, Y.K., R.W. and R.C.; Methodology, Y.K. and L.V.; Writing—original draft, Y.K.; Writing—review and editing, Y.K., L.V., R.W. and R.C.; Supervision, R.C. All authors have read and agreed to the published version of the manuscript.

Funding: CONSUS is funded under the SFI Strategic Partnership Programme (16/SPP/3296) and is co-funded by Origin Enterprises plc. (Dublin, Ireland).

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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

Abbreviations

The following abbreviations are used in this manuscript:

API	Application programming interfaces
CEA	Closed Environment Agriculture
DT	Digital twin
GUI	Graphical User Interface
IoT	Internet of Things
MAS	Multi-agent systems
MAMS	Multi-agent Micro-services
OEA	Open Environment Agriculture
NDVI	Normalized Difference Vegetation Index
UAV	Unmanned Aerial Vehicles

References

1. Dagar, R.; Som, S.; Khatri, S.K. Smart farming–IoT in agriculture. In Proceedings of the 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 11–12 July 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1052–1056.
2. Kalyani, Y.; Collier, R. A systematic survey on the role of cloud, fog, and edge computing combination in smart agriculture. *Sensors* **2021**, *21*, 5922. [CrossRef] [PubMed]
3. Rose, D.C.; Chilvers, J. Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Front. Sustain. Food Syst.* **2018**, *2*, 87. [CrossRef]

4. Saiz-Rubio, V.; Rovira-Más, F. From smart farming towards agriculture 5.0: A review on crop data management. *Agronomy* **2020**, *10*, 207. [CrossRef]
5. Nasirahmadi, A.; Hensel, O. Toward the next generation of digitalization in agriculture based on digital twin paradigm. *Sensors* **2022**, *22*, 498. [CrossRef]
6. Farooq, M.S.; Riaz, S.; Abid, A.; Abid, K.; Naeem, M.A. A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming. *IEEE Access* **2019**, *7*, 156237–156271. [CrossRef]
7. Osinga, S.A.; Paudel, D.; Mouzakitis, S.A.; Athanasiadis, I.N. Big data in agriculture: Between opportunity and solution. *Agric. Syst.* **2022**, *195*, 103298. [CrossRef]
8. Liakos, K.G.; Busato, P.; Moshou, D.; Pearson, S.; Bochtis, D. Machine learning in agriculture: A review. *Sensors* **2018**, *18*, 2674. [CrossRef]
9. Hurst, W.; Mendoza, F.R.; Tekinerdogan, B. Augmented reality in precision farming: Concepts and applications. *Smart Cities* **2021**, *4*, 1454–1468. [CrossRef]
10. Lytridis, C.; Kaburlasos, V.G.; Pachidis, T.; Manios, M.; Vrochidou, E.; Kalampokas, T.; Chatzistamatis, S. An overview of cooperative robotics in agriculture. *Agronomy* **2021**, *11*, 1818. [CrossRef]
11. Verdouw, C.; Tekinerdogan, B.; Beulens, A.; Wolfert, S. Digital twins in smart farming. *Agric. Syst.* **2021**, *189*, 103046. [CrossRef]
12. Chaux, J.D.; Sanchez-Londono, D.; Barbieri, G. A digital twin architecture to optimize productivity within controlled environment agriculture. *Appl. Sci.* **2021**, *11*, 8875. [CrossRef]
13. Ghandar, A.; Ahmed, A.; Zulfiqar, S.; Hua, Z.; Hanai, M.; Theodoropoulos, G. A decision support system for urban agriculture using digital twin: A case study with aquaponics. *IEEE Access* **2021**, *9*, 35691–35708. [CrossRef]
14. Monteiro, J.; Barata, J.; Veloso, M.; Veloso, L.; Nunes, J. A scalable digital twin for vertical farming. *J. Ambient. Intell. Humaniz. Comput.* **2023**, *14*, 13981–13996. [CrossRef]
15. Sreedevi, T.; Kumar, M.S. Digital Twin in Smart Farming: A categorical literature review and exploring possibilities in hydroponics. In Proceedings of the 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), Cochin, India, 2–4 July 2020; pp. 120–124.
16. Le Mouël, C.; Forslund, A. How can we feed the world in 2050? A review of the responses from global scenario studies. *Eur. Rev. Agric. Econ.* **2017**, *44*, 541–591. [CrossRef]
17. Honc, D.; Merta, J. Smart, precision or digital agriculture and farming-current state of technology. In Proceedings of the 15th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2020) 15, Burgos, Spain, 16–18 September 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 245–254.
18. Abdalla, Z.F.; El-Ramady, H. Applications and Challenges of Smart Farming for Developing Sustainable Agriculture. *Environ. Biodivers. Soil Secur.* **2022**, *6*, 81–90. [CrossRef]
19. Zhai, Z.; Martínez, J.F.; Beltran, V.; Martínez, N.L. Decision support systems for agriculture 4.0: Survey and challenges. *Comput. Electron. Agric.* **2020**, *170*, 105256. [CrossRef]
20. Tien, J.M. Internet of things, real-time decision making, and artificial intelligence. *Ann. Data Sci.* **2017**, *4*, 149–178. [CrossRef]
21. Grieves, M. Digital twin: Manufacturing excellence through virtual factory replication. *White Pap.* **2014**, *1*, 1–7.
22. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
23. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *Ifac-PapersOnline* **2018**, *51*, 1016–1022. [CrossRef]
24. Erol, T.; Mendi, A.F.; Doğan, D. The digital twin revolution in healthcare. In Proceedings of the 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Istanbul, Turkey, 22–24 October 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 1–7.
25. Sleiti, A.K.; Kapat, J.S.; Vesely, L. Digital twin in energy industry: Proposed robust digital twin for power plant and other complex capital-intensive large engineering systems. *Energy Rep.* **2022**, *8*, 3704–3726. [CrossRef]
26. Schrotter, G.; Hürzeler, C. The digital twin of the city of Zurich for urban planning. *PFG–J. Photogramm. Remote Sens. Geoinf. Sci.* **2020**, *88*, 99–112. [CrossRef]
27. Pylianidis, C.; Osinga, S.; Athanasiadis, I.N. Introducing digital twins to agriculture. *Comput. Electron. Agric.* **2021**, *184*, 105942. [CrossRef]
28. Skobelev, P.; Laryukhin, V.; Simonova, E.; Goryanin, O.; Yalovenko, V.; Yalovenko, O. Developing a smart cyber-physical system based on digital twins of plants. In Proceedings of the 2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), London, UK, 27–28 July 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 522–527.
29. Purcell, W.; Neubauer, T.; Mallinger, K. Digital Twins in agriculture: Challenges and opportunities for environmental sustainability. *Curr. Opin. Environ. Sustain.* **2023**, *61*, 101252. [CrossRef]
30. Sunyaev, A. Cloud computing. In *Internet Computing: Principles of Distributed Systems and Emerging Internet-Based Technologies*; Springer: Cham, Switzerland, 2020; pp. 195–236.
31. Basir, R.; Qaisar, S.; Ali, M.; Aldwairi, M.; Ashraf, M.I.; Mahmood, A.; Gidlund, M. Fog computing enabling industrial internet of things: State-of-the-art and research challenges. *Sensors* **2019**, *19*, 4807. [CrossRef]
32. Zhang, R.; Li, X. Edge computing driven data sensing strategy in the entire crop lifecycle for smart agriculture. *Sensors* **2021**, *21*, 7502. [CrossRef] [PubMed]

33. Hazra, A.; Rana, P.; Adhikari, M.; Amgoth, T. Fog computing for next-generation internet of things: Fundamental, state-of-the-art and research challenges. *Comput. Sci. Rev.* **2023**, *48*, 100549. [CrossRef]
34. Kalyani, Y.; Bermeo, N.V.; Collier, R. Digital twin deployment for smart agriculture in Cloud-Fog-Edge infrastructure. *Int. J. Parallel Emergent Distrib. Syst.* **2023**, *38*, 461–476. [CrossRef]
35. Sethi, V.; Pal, S. FedDOVe: A Federated Deep Q-learning-based Offloading for Vehicular fog computing. *Future Gener. Comput. Syst.* **2023**, *141*, 96–105. [CrossRef]
36. Silva, L.; Rodríguez-Sedano, F.; Baptista, P.; Coelho, J.P. The Digital Twin Paradigm Applied to Soil Quality Assessment: A Systematic Literature Review. *Sensors* **2023**, *23*, 1007. [CrossRef]
37. Angin, P.; Anisi, M.H.; Göksel, F.; Gürsoy, C.; Büyükgülcü, A. AgriLoRa: A digital twin framework for smart agriculture. *J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl.* **2020**, *11*, 77–96.
38. Skobelev, P.; Simonova, E.; Tabachinskiy, A.; Kudryakov, E.; Strizhakov, A.; Goryanin, O.; Ermakov, V.; Chan, Y.K.; Lee, T.R.; Sung, Y. Concept and Development of a Multi-Agent Digital Twin of Plant Focused on Broccoli. In Proceedings of the 2023 7th International Conference on Intelligent Systems, Metaheuristics & Swarm Intelligence, Virtual Event, Malaysia, 23–24 April 2023; pp. 132–138.
39. Collier, R.W.; O'Neill, E.; Lillis, D.; O'Hare, G. MAMS: Multi-Agent MicroServices. In Proceedings of the Companion Proceedings of the 2019 World Wide Web Conference, Montreal, QC, Canada, 25–31 May 2019; pp. 655–662.
40. García, L.; Parra, L.; Jimenez, J.M.; Lloret, J.; Lorenz, P. IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors* **2020**, *20*, 1042. [CrossRef] [PubMed]
41. Arumugam, S.S.; Ganeshmurthi, M.; Annadurai, R.; Ravichandran, V. Internet of things based smart agriculture. *Int. J. Adv. Comput. Electron. Eng.* **2018**, *33*, 8–17.
42. Rao, R.N.; Sridhar, B. IoT based smart crop-field monitoring and automation irrigation system. In Proceedings of the 2018 2nd International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 19–20 January 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 478–483.
43. Iglesias, A.; Santillán, D.; Garrote, L. On the barriers to adaption to less water under climate change: Policy choices in Mediterranean countries. *Water Resour. Manag.* **2018**, *32*, 4819–4832. [CrossRef]
44. Kundu, R.; Dutta, D.; Chakrabarty, A.; Nanda, M.K. Spatial growth pattern of potato in West Bengal using multi-temporal MODIS NDVI Data. *Int. J. Comput. Sci. Eng.* **2018**, *6*, 52–59. [CrossRef]
45. Peters, A.J.; Walter-Shea, E.A.; Ji, L.; Vina, A.; Hayes, M.; Svoboda, M.D. Drought monitoring with NDVI-based standardized vegetation index. *Photogramm. Eng. Remote Sens.* **2002**, *68*, 71–75.
46. Shankar, T.; Banerjee, M.; Malik, G.C.; Dutta, S.; Maiti, D.; Maitra, S.; Alharby, H.; Bamagoos, A.; Hossain, A.; Ismail, I.A.; et al. The productivity and nutrient use efficiency of rice–rice–black gram cropping sequence are influenced by location specific nutrient management. *Sustainability* **2021**, *13*, 3222. [CrossRef]
47. Dhakal, C.; Lange, K. Crop yield response functions in nutrient application: A review. *Agron. J.* **2021**, *113*, 5222–5234. [CrossRef]
48. Sanjuan-Delmás, D.; Josa, A.; Muñoz, P.; Gassó, S.; Rieradevall, J.; Gabarrell, X. Applying nutrient dynamics to adjust the nutrient-water balance in hydroponic crops. A case study with open hydroponic tomato crops from Barcelona. *Sci. Hortic.* **2020**, *261*, 108908. [CrossRef]
49. Agrahari, R.K.; Kobayashi, Y.; Tanaka, T.S.T.; Panda, S.K.; Koyama, H. Smart fertilizer management: The progress of imaging technologies and possible implementation of plant biomarkers in agriculture. *Soil Sci. Plant Nutr.* **2021**, *67*, 248–258. [CrossRef]
50. Inoue, Y. Satellite-and drone-based remote sensing of crops and soils for smart farming—A review. *Soil Sci. Plant Nutr.* **2020**, *66*, 798–810. [CrossRef]
51. Shaikh, T.A.; Rasool, T.; Lone, F.R. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comput. Electron. Agric.* **2022**, *198*, 107119. [CrossRef]
52. Dhanaraju, M.; Chenniappan, P.; Ramalingam, K.; Pazhanivelan, S.; Kaliaperumal, R. Smart farming: Internet of Things (IoT)-based sustainable agriculture. *Agriculture* **2022**, *12*, 1745. [CrossRef]