

Systematic Review

Harnessing Digital Twins for Sustainable Agricultural Water Management: A Systematic Review

Rameez Ahsen ¹, Pierpaolo Di Bitonto ¹ , Pierfrancesco Novielli ^{1,2} , Michele Magarelli ¹ , Donato Romano ^{1,2} , Domenico Diacono ² , Alfonso Monaco ^{2,3}, Nicola Amoroso ^{2,4} , Roberto Bellotti ^{2,3} and Sabina Tangaro ^{1,2,*} 

- ¹ Dipartimento di Scienze del Suolo, della Pianta e degli Alimenti, Università degli Studi di Bari Aldo Moro, 70125 Bari, Italy; rameez.ahsen@uniba.it (R.A.); pierpaolo.dibitonto@uniba.it (P.D.B.); pierfrancesco.novielli@uniba.it (P.N.); michele.magarelli@uniba.it (M.M.); donato.romano@uniba.it (D.R.)
- ² Istituto Nazionale di Fisica Nucleare, Sezione di Bari, 70125 Bari, Italy; domenico.diacono@ba.infn.it (D.D.); alfonso.monaco@uniba.it (A.M.); nicola.amoroso@uniba.it (N.A.); roberto.bellotti@uniba.it (R.B.)
- ³ Dipartimento Interateneo di Fisica “M. Merlin”, Università degli Studi di Bari Aldo Moro, 70125 Bari, Italy
- ⁴ Dipartimento di Farmacia-Scienze del Farmaco, Università degli Studi di Bari Aldo Moro, 70125 Bari, Italy
- * Correspondence: sabina.tangaro@uniba.it

Abstract: This systematic review explores the use of digital twins (DT) for sustainable agricultural water management. DTs simulate real-time agricultural environments, enabling precise resource allocation, predictive maintenance, and scenario planning. AI enhances DT performance through machine learning (ML) and data-driven insights, optimizing water usage. In this study, from an initial pool of 48 papers retrieved from well-known databases such as Scopus and Web of Science, etc., a rigorous eligibility criterion was applied, narrowing the focus to 11 pertinent studies. This review highlights major disciplines where DT technology is being applied: hydroponics, aquaponics, vertical farming, and irrigation. Additionally, the literature identifies two key sub-applications within these disciplines: the simulation and prediction of water quality and soil water. This review also explores the types and maturity levels of DT technology and key concepts within these applications. Based on their current implementation, DTs in agriculture can be categorized into two functional types: monitoring DTs, which emphasize real-time response and environmental control, and predictive DTs, which enable proactive irrigation management through environmental forecasting. AI techniques used within the DT framework were also identified based on their applications. These findings underscore the transformative role that DT technology can play in enhancing efficiency and sustainability in agricultural water management. Despite technological advancements, challenges remain, including data integration, scalability, and cost barriers. Further studies should be conducted to explore these issues within practical farming environments.

Keywords: digital twin; artificial intelligence; machine learning; precision agriculture



Academic Editor: José Miguel Molina Martínez

Received: 22 January 2025

Revised: 2 April 2025

Accepted: 8 April 2025

Published: 11 April 2025

Citation: Ahsen, R.; Di Bitonto, P.; Novielli, P.; Magarelli, M.; Romano, D.; Diacono, D.; Monaco, A.; Amoroso, N.; Bellotti, R.; Tangaro, S. Harnessing Digital Twins for Sustainable Agricultural Water Management: A Systematic Review. *Appl. Sci.* **2025**, *15*, 4228. <https://doi.org/10.3390/app15084228>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Agriculture holds a pivotal role in global economies and societies and is fundamental to human survival and development. Agricultural practices influence environmental sustainability, impacting soil health, water resources, and biodiversity. Understanding and innovating in agricultural practices is crucial for addressing global challenges such as food security, rural development, and sustainable resource management.

Key agricultural inputs—fertilizers, agrochemicals, and water—are critical for enhancing crop productivity [1]. The effective management of these resources is essential

to ensure agricultural sustainability and environmental protection. Water stands as the most utilized input among these resources [2], playing a vital role in crop irrigation. However, water scarcity is one of the most pressing challenges of our time, with significant implications for crop yield and food security [3]. Efficient irrigation systems and sustainable farming practices are crucial in mitigating the impact of water scarcity on agriculture. An improper management of irrigation development can lead to the dual challenges of rising aquifer levels and increased salinization in irrigated areas [4]. Various strategies can be explored to address this problem. But, due to the site-specific nature of these solutions, field experiments alone are insufficient to fully validate their effectiveness [5]. Precision irrigation systems now deliver water directly to crop roots, reducing water loss from evaporation and runoff [6,7]. Additionally, emerging innovations such as microturbine technology have shown potential for enhancing energy efficiency and resource management in agricultural irrigation systems [8].

In recent decades, artificial intelligence (AI) has increasingly been adopted in the agricultural sector, significantly improving agronomic practices [9]. Whether it is in the field of genome-to-phenome prediction, soil health, farm machinery, or water management, AI is proving to be transformative [10–12]. Predicting phenotypic traits from genomic data remains a challenge, but AI combined with machine learning (ML) enhances accuracy and efficacy in this area, optimizing crop production [13]. In soil health, AI has been employed to predict nutrient availability and microbial respiration sensitivity, elucidating the role of the microbiome and environmental factors in the soil carbon cycle [14]. In farm machinery, AI is being used to design and automate operations for tractors, harvesters, and sprayers, improving efficiency and precision [12]. In water management, the precision prediction of water needs and irrigation practices is advancing, driven by AI-enabled tools and technologies [15]. In particular, the development of computer-based technologies such as simulations, digital models (DMs), remote sensing (RS) data, Geographic Information Systems (GISs), ML, deep learning (DL), and the Internet of Things (IoT) has greatly enhanced the understanding of parameters characterizing water resource management. Simultaneously, digitalization has become increasingly prominent, with the adoption of new technologies and concepts such as smart agriculture, precision farming, and, more recently, digital twins (DTs).

In the agricultural sector, the adoption of DT technology is steadily increasing [16], but it is still less mature compared to fields like manufacturing [17]. This lag is due to the unique complexity of agriculture, which involves the interaction of climatic conditions, living organisms, and non-living physical elements [18]. Although artificial intelligence (AI) is not yet widely applied in agriculture, its potential is immense. The integration of AI with DTs could revolutionize the sector, thanks to AI's ability to analyze large volumes of data, identify complex patterns, and make accurate predictions. In particular, AI can improve water resource management, optimize irrigation cycles, predict adverse weather conditions, and monitor crop health in real time [9]. The benefits of combining AI and DTs in agriculture are manifold. AI can leverage virtual models created by DTs to simulate future scenarios, predict issues like drought or crop diseases, and provide targeted solutions [19]. This approach would enhance operational efficiency, reduce resource waste, and allow farmers to make more informed and timely decisions. Furthermore, AI can help optimize the use of fertilizers and pesticides, reducing environmental impact and increasing the sustainability of agricultural practices [20]. In summary, AI, when used in conjunction with DTs, can offer innovative solutions to address the complex challenges of modern agriculture, bringing significant benefits in terms of productivity, efficiency, and sustainability.

Although various studies have explored DT applications in broader agricultural contexts and covered general technical aspects, supply chain performance, precision agriculture, and smart farming frameworks [19,21–27], they often fail to specifically address the critical aspect of water management. Furthermore, the existing literature frequently overlooks the maturity levels of DT technology in agricultural water management. This lack of targeted research leaves a gap in understanding how DTs can optimize water use, thereby enhancing crop yields and sustainability.

To address this research gap, this review aims to provide a comprehensive analysis of the development and application of DTs specifically in the context of agricultural water management. By meticulously screening and synthesizing the relevant scientific literature, this study seeks to encompass a wide range of crucial aspects. These include the specific tools and techniques employed in DT systems, the types of farms and environments where these systems are applied, and the maturity levels of the developed technologies. This thorough examination will offer a detailed understanding of the current state of DT technology in agricultural water management and identify potential areas for future research and development. After the Introduction, Section 2 describes the background. Section 3 covers the research methodology, which consists of the research questions and eligibility criteria applied to find studies in the literature for review. Section 4 shows the results of the applied methodology, the types of DTs, the integration of AI, the available tools, the maturity level of DT technology in agriculture water, key concepts, and a discussion. Sections 5 and 6 provide the discussion and conclusion, respectively.

2. Background

2.1. AI and Digital Twins

DT technology is an emerging innovation in agriculture that has the potential to revolutionize resource management, particularly when integrated with AI. DTs create digital replicas of physical agricultural systems, enabling accurate simulations and an optimized management of key parameters such as irrigation, fertilization, humidity, and soil resource availability. With AI, these simulations can be continuously updated and improved by analyzing large volumes of data, making decision-making more efficient. The integration of DTs with AI is one of the most promising advancements in modern agriculture. DTs allow for the real-time simulation of crop growth and resource optimization through the continuous monitoring and precise modeling [28] of environmental and agronomic variables. When combined with ML, DTs can significantly enhance agricultural productivity by improving decision accuracy and reducing resource wastage, including water, fertilizers, and pesticides. AI, through data from sensors, satellites, and drones, can analyze large datasets to identify complex patterns and make accurate predictions [29]. This integration enables the optimal management of variables like plant spacing, water availability, soil quality, and light intensity, ultimately improving both productivity and sustainability. AI-driven DT models can solve complex problems, such as determining optimal agricultural parameters to maximize yields while minimizing resource usage. An example of this synergy is irrigation optimization. AI combined with DT models can analyze real-time field data to monitor soil moisture levels and plant growth, allowing for dynamic irrigation adjustments that prevent water wastage and mitigate drought risks [30]. This technology is particularly beneficial in the context of increasing water scarcity. DTs also play a crucial role in predicting adverse weather events and managing crop diseases. By analyzing meteorological and biological data, DTs can forecast storms, heat waves, or humidity conditions [31] that promote disease spread, allowing for preventive measures like targeted fungicide application. As noted by Rajmis et al. [32], this approach can save costs up to 50 percent, lowering operational costs. Moreover, DTs offer the ability to simulate future

scenarios, allowing farmers to test different cultivation strategies and optimize resource use, reducing environmental impact and enhancing sustainability. This technology can reduce pesticide use, promoting more sustainable agricultural practices. DTs also optimize agricultural supply chains by synchronizing production with market demand, improving logistics, and reducing food waste [33].

2.2. Remote Sensing and Digital Twins

Satellite and UAV technologies are good for monitoring large-scale agricultural systems and supporting the creation of digital twins (DTs). Remote sensing (RS) data are essential for virtualization and offer valuable insights into crop conditions and resource needs. However, the effectiveness of satellite imagery in agriculture is often limited due to spatial and temporal resolution constraints. UAVs, equipped with advanced sensors such as RGB, multispectral, hyperspectral, and LiDAR, provide a complementary approach, offering higher-resolution data tailored for precision agriculture [34] where traditional low-resolution RS data may fall short. High-resolution RS data are beneficial; however, they significantly increase data volume. Traditionally, RS has been used for generating land use land cover (LULC) maps, analyzing soil properties, assessing crop health, and optimizing irrigation. Recent advancements in data fusion techniques allow for the combination of high-spatial- and low-temporal-resolution data from multiple satellite sources, enabling more comprehensive and timely information [35]. Integrating satellite data with DT models advances agricultural monitoring capabilities by providing real-time insights and detailed, three-dimensional virtual representations of agricultural landscapes, including terrain and canopy structures [27]. These virtual models enable improved decision-making by offering a more in-depth view of environmental interactions.

DTs are also increasingly applied in water resource management, with notable implementations for flood and hazardous assessments [36]. For instance, Brocca et al. [37] developed a DT for flood prediction using high-resolution satellite data, while Chen et al. [38] utilized digital elevation models (DEMs) to construct a DT for wetland environmental studies. Such applications highlight the versatility of DT technology across various environmental domains. In specific cases, like modeling the Poyang Lake wetland, DTs simulate typical wetland environments, showcasing how these virtual models can support both environmental conservation and resource management in agriculture, offering a robust foundation for sustainable practices.

2.3. DT Architecture

A comprehensive and foundational framework for the first DT was established in 2014, marking a significant milestone in the field. This framework encapsulates not only the physical realm but also extends to the virtual realm, highlighting the intricate connection that acts as a crucial link between them [39]. While effective for basic monitoring and visualization, this model lacks the depth to support advanced capabilities such as intelligent control, predictive maintenance and closed-loop feedback.

Stark et al. [40] described DTs as a unique digital representation of a physical asset, composed of three key elements. The Digital Master refers to the static, model-based design of the asset. The Digital Shadow captures real-time operational and condition data collected from the physical system. These two components are connected through an intelligent linkage, which includes algorithms, simulations, and decision-making processes. This structured separation enables more advanced behavior modeling, supports simulation-based optimization, and allows for continuous system learning. As a result, the three-layer DT architecture is well suited for the evolving demands of Cyber-Physical Production Systems (CPPS). This three-layer DT lacked explicit mechanisms for managing

services and handling large-scale, heterogeneous data for Prognostics and Health Management (PHM). To address this gap, Tao et al. [41] presented an extended five-layer DT model, which has two extended layers, a Service Layer to model and manage functional operations like monitoring, calibration, and fault diagnosis, and a Data Layer to integrate and fuse data from physical systems, simulations, services, and domain knowledge. So, this DT has the ability to handle data from multiple sensors.

Further contributions to the development of DT architectures include the five-layer DT model by Ponomarev K et al. [42]. This DT is quite different from the previous extended five-layer DT. While Tao et al.'s architecture was mainly designed for managing PHM, Ponomarev's model takes a more system-level, IT-focused approach that spans from CPS to distributed computing and user interfaces. It introduces practical elements such as APIs, cloud-based storage systems, and visualization platforms. This kind of structure is more suitable for industrial environments where systems are complex and need to be monitored, controlled, and updated in real time. These DTs focused on system modeling, data storage, and user interaction. However, they lacked sufficient granularity to separate edge-device logic, communication handling, and simulation intelligence. Further, Redelinghus et al. [43] introduced an extended six-layer DT structure by isolating control logic, local data storage, IoT gateways, cloud databases, and simulation components. The introduction of a dedicated IoT gateway layer plays a pivotal role, enabling data filtering, conflict resolution, safety validation, and efficient transformation between local and cloud data. This enhancement addresses the limitations of earlier models by facilitating bidirectional, secure, and scalable communication between physical and cyber spaces. This DT architecture is more suitable for applications involving multiple interconnected DTs. The differences between the DT architectures defined above are described in Figure 1.

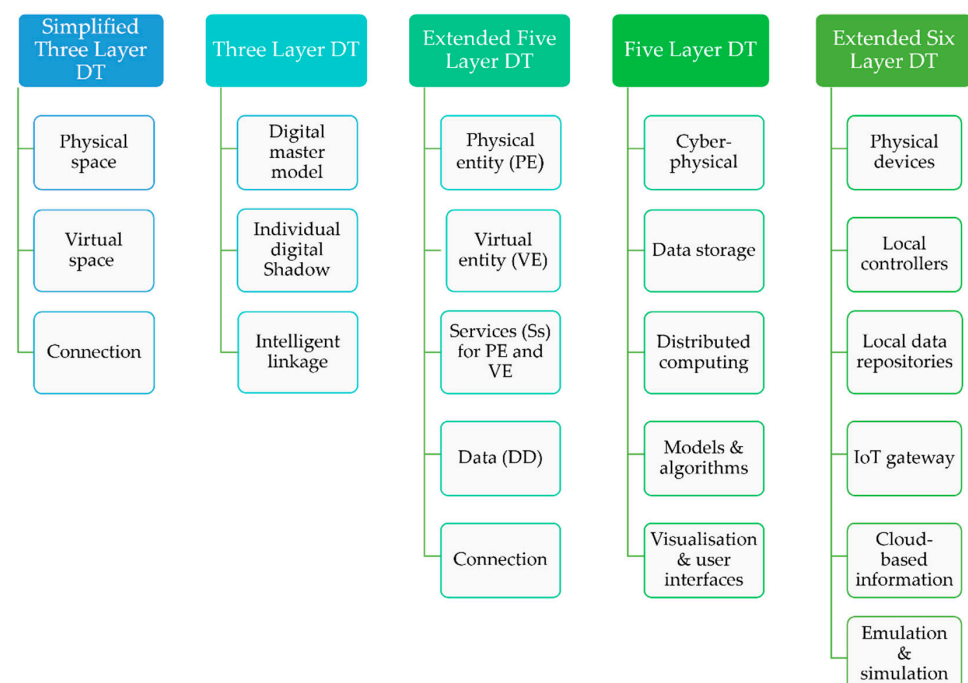


Figure 1. Layer-wise evolution of DT architectures from simplified to extended models synthesized from the literature.

The DT architecture can be conceptualized as a structure with three main layers [44]. The first one is a physical layer: the physical layer encompasses real-world entities, categorized according to their stage in the product life cycle. The second is a network layer, which acts as a bridge between the physical and digital domains, enabling data exchange

and communication. The third is a computing layer, which includes digital representations of real entities, utilizing data-driven and physics-based models, along with analytics, services, and user interfaces. Each layer contains specific DT components (such as hardware, software, models, and information frameworks) that share common objectives and interactions, offering complementary functions [45].

2.3.1. Real-Time Monitoring

The adoption of smart technologies in agriculture is on the rise [46], transforming farms into systems that operate intelligently. These systems use a variety of tools to sense and monitor environmental conditions and manage farming equipment effectively [47]. Agricultural water management can be categorized into monitoring and control strategies. Monitoring strategies include soil moisture, weather, and vegetative parameters, and control strategies include open-loop and closed-loop methods [48]. The open-loop method involves a predetermined schedule or set of rules for irrigation, without real-time feedback from the environment, while the closed-loop method, on the other hand, involves the monitoring and dynamic adjustment of irrigation based on continuous feedback from sensors [49]. Designing DTs is among the most sophisticated approaches for creating an intelligent system for monitoring and control [50]. As discussed above, a DT is a virtual representation of physical objects, so DTs enable real-time interaction between a physical object and its digital counterpart. Modifications in the physical object are automatically reflected in the digital model, and vice versa [51].

2.3.2. Collection and Integration of Data from Multiple Sources

Researchers have measured soil moisture using various methods, including soil moisture sensors, thermal imaging, and remote sensing techniques [52–54]. Sensors and remote sensing data can be integrated with DTs to continuously gather data from the physical environment [55,56]. These real-time data keep the DT updated and enhances decision-making.

The Internet of Things (IoT) is the network of linked physical devices equipped with sensors, an IoT platform, and user interfaces, allowing them to gather and share data over the internet autonomously, without human intervention [57]. The adoption of IoT technology in the agriculture sector is growing rapidly [58]. This technology enhances efficiency, reduces waste, and supports sustainable farming practices [59]. IoT-based smart sensors collect data on soil moisture, temperature, wind, and humidity, which are then analyzed to assess the soil's water needs.

Recent advancements in sensor technologies have greatly improved the quality and accessibility of remote sensing data. These data play a key role in monitoring floods, managing water resources, and in soil and water conservation efforts in agriculture. Satellite-based remote sensing technologies enable the near-real-time provision of spatio-temporal information for fields. Irrigation, as the primary consumer of agricultural water, benefits significantly from these developments. Unlike IoT sensors, which provide point-source soil moisture data and may not capture the variability across a diverse agricultural environment, remote sensing offers a broader solution. With high-resolution imagery, it can deliver pixel-level data, representing conditions across small areas and plants. Earth observation satellites offer an innovative and efficient method for monitoring soil moisture and other field variables like evapotranspiration [60]. Indices like Normalized Difference Vegetation Index (NDVI) are commonly applied with crop coefficients (K_c), essential for determining crop water requirements [61]. Furthermore, Surface Energy Balance (SEB) methods are used to provide more accurate soil moisture estimates [62]. Satellite imagery also aids in mapping landscape features like soil type and slope, which are useful for soil moisture [63]; when combined with IoT sensor data, it enhances the accuracy. ML tech-

niques analyze data by automating data processing, segmentation, and feature extraction. This advanced method streamlines the analysis of large datasets, enabling an efficient and accurate identification of key features and patterns within the data, ultimately enhancing decision-making processes [64]. Now, estimating evapotranspiration [65] and soil moisture [66] using remote sensing is a well-established method in agricultural water management. This approach leverages satellite and aerial imagery to monitor and assess water needs, ensuring efficient irrigation practices and optimizing water use for improved crop health and yield.

2.3.3. Simulation and Modeling of Various Scenarios

DT technology offers a transformative approach by enabling the simulation and modeling of various water management scenarios [67,68], such as droughts [69], floods [70], and optimized irrigation schedules [71]. This innovative application leverages real-time data, advanced analytics, and predictive models to enhance decision-making, conserve resources, and ensure agricultural sustainability. A simple structure of a DT in the context of farm water management can be seen in Figure 2. In the context of agricultural water management, DT technology can be employed for simulating and modeling water quality in hydroponics and aquaponics, analyzing soil water dynamics, predicting water stress on plants, and optimizing irrigation scheduling systems.

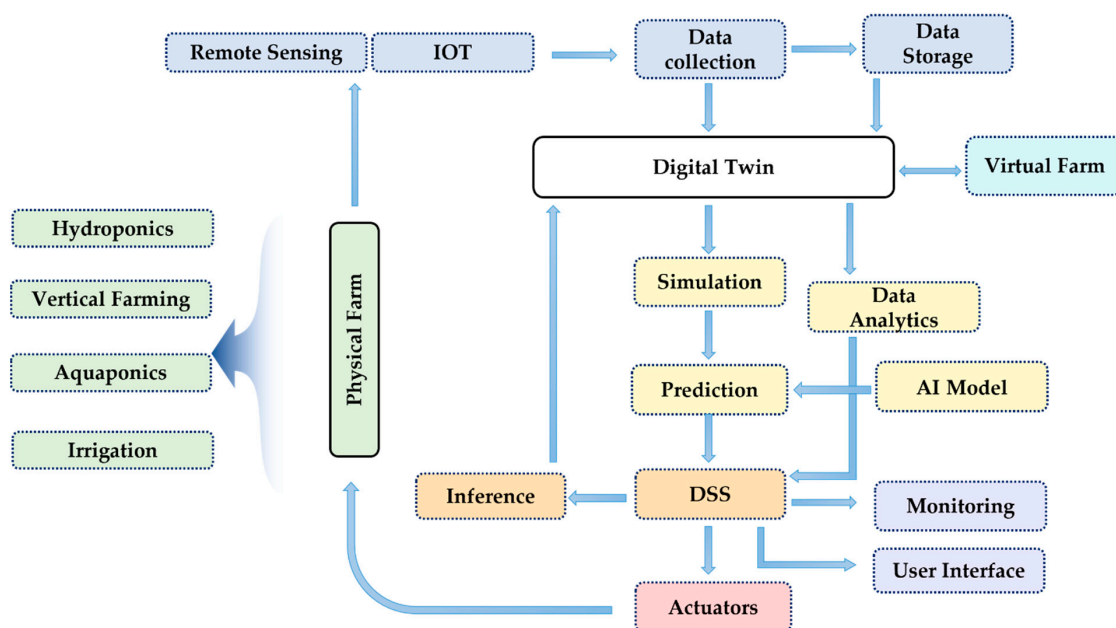


Figure 2. DT framework for on-farm water management integrating physical systems with virtual monitoring, data management, and decision support.

3. Materials and Methods

This systematic literature review (SLR) was conducted in accordance with the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [72], which are intended to improve the transparency, consistency, and completeness of systematic reviews. The PRISMA framework outlines essential components for reporting, including the rationale for the review, comprehensive search strategies, eligibility criteria, data collection methods, and synthesis of results. Following these guidelines ensures methodological rigor and facilitates reproducibility, which are critical for the credibility of evidence-based research.

3.1. Research Questions and Databases Searched

A review protocol was established before the bibliographic analysis to systematically identify, assess, and interpret findings relevant to the research focus. First, this review investigates the current applications of DTs in agricultural water management, aiming to understand the existing scope and practical implementations of DTs. Then, the focus shifts to exploring the types of DT models utilized in this domain, providing insights into their functionalities and their suitability and adaptability for different water scenarios. Further, the integration of AI with DTs is examined, along with the outcomes achieved through this combination. This helps evaluate the potential of AI to enhance the predictive and analytical capabilities of DT systems. Finally, this review extends to assessing the extent to which DTs have been applied, including the tools, techniques, the maturity levels of the systems, and identifying the key benefits associated with implementing DT technologies in precision agriculture water management. Highlighting these benefits emphasizes DTs' potential to improve resource efficiency and decision-making. These interconnected focal areas collectively form a comprehensive framework for reviewing the existing literature and advancing the understanding of DTs in water management practices.

Next, a search strategy was devised to pinpoint the appropriate keywords for the search string, with the goal of identifying relevant information sources, such as academic databases and search engines that provide extensive digital documentation. Figure 3 depicts the step-by-step process for extracting studies from prominent scientific research databases, including Scopus, Web of Science (WoS), ScienceDirect, and IEEE Xplore. Specific search strings were employed by the authors in these databases to locate pertinent research on DTs. The following string was used to search the literature after modifications relevant to each database: ("Water") AND ("digital twin") AND (Agri* OR "smart farming" OR "crop" OR "Precision").

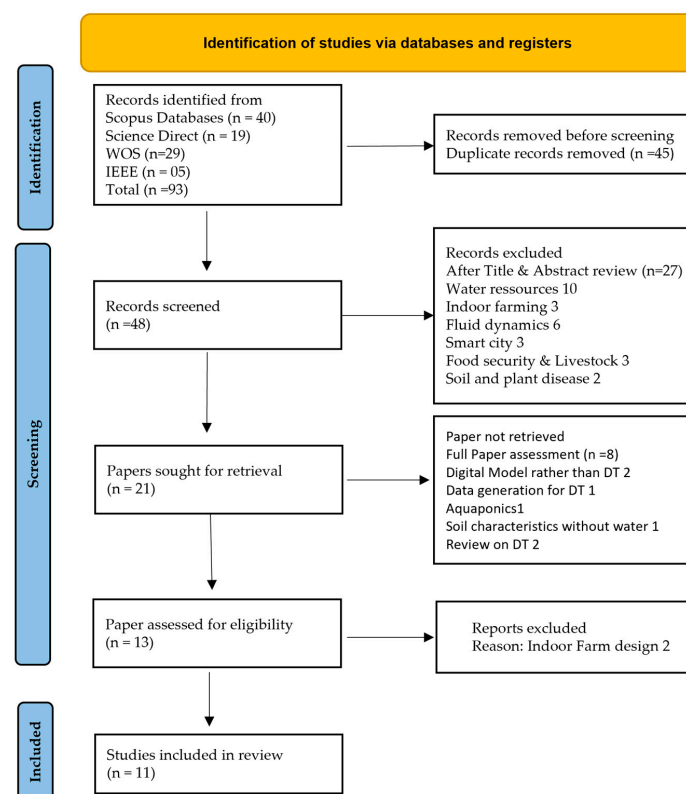


Figure 3. PRISMA flow diagram for literature review.

3.2. Eligibility Criteria

Finally, to narrow down the search results from each database, the inclusion and exclusion criteria were predetermined. These criteria help to focus the investigation and evaluate the content of the selected publications. The inclusion criteria for the study required that only peer-reviewed journal articles in English be selected, with a primary focus on agricultural water management in the context of DT technology. Additionally, the studies needed to provide relevant answers to the research questions. The exclusion criteria ruled out conference papers, event and seminar summaries, book reviews, editorials, articles not in English, and publications that were not available in full text.

The literature search process was evaluated through three stages—identification, screening and inclusion—as depicted in the PRISMA flow diagram in Figure 3. After filtering the initial metadata, in total, 93 records were identified (40 from Scopus, 19 from ScienceDirect, 29 from WoS, and 5 from IEEE Xplore). Then, duplicates were removed during the identification stage, reducing the total to 48 publications. In the screening stage, titles and abstracts were reviewed,

Some studies initially appeared relevant because their titles, abstracts, or keywords included terms like ‘digital twin’, ‘water’, and ‘agriculture’. However, after carefully reviewing their titles and abstracts, we found that these articles did not specifically address our main objective, i.e., exploring the use of DT technology for agricultural water management. Instead, these papers covered broader or indirectly related topics, such as flood management, water conservation, indoor farming, livestock management, construction, energy management, and soil characteristics. Although these topics have some indirect links to agriculture or water management, they did not clearly focus on DT applications specifically for managing water resources on farms. Therefore, we excluded these 27 studies at this stage to ensure our review remained targeted and relevant.

After narrowing down our search to 21 papers for a full-text review, we carefully examined each one to see how well they aligned with our research questions. We focused on three key aspects: whether the study truly involved a DT, the type of application, and its practical relevance to agricultural water management. Some papers described digital simulations or models as DTs. Other studies discussed applications like indoor farming or fish farm design, which, although related to agriculture, do not directly deal with water management on farms. We also excluded articles focused solely on topics such as soil characteristics, yield estimation, general agricultural data collection for DTs, or general reviews that lacked clear, practical field applications specific to water management. After applying these criteria, we excluded 10 studies, leaving a final selection of 11 papers.

4. Results

This section presents the data extracted during the systematic literature review process, covering both the planning and conduction phases. The results are subsequently presented, followed by a corresponding analysis and discussion.

Research on the application of DTs in agriculture began to emerge around 2021, but the pace of publications indicates relatively modest growth over the subsequent years. Starting with only a single publication in 2021, the number increased slightly to two publications in 2022 and then reached four publications each in 2023 and 2024. Despite this gradual upward trend, the limited volume of research suggests that the technology has yet to achieve broad recognition or widespread adoption within the agricultural water management field. Overall, the data show a growing acceptance of studies on DT technology in agricultural water management, emphasizing its growing significance and potential to improve efficiency.

4.1. DT Application in Agricultural Water Management

Despite the number of publications, research papers specifically addressing crop water management are very limited, amounting to only 11 papers. Figure 4 presents the crop area-wise distribution of these publications.

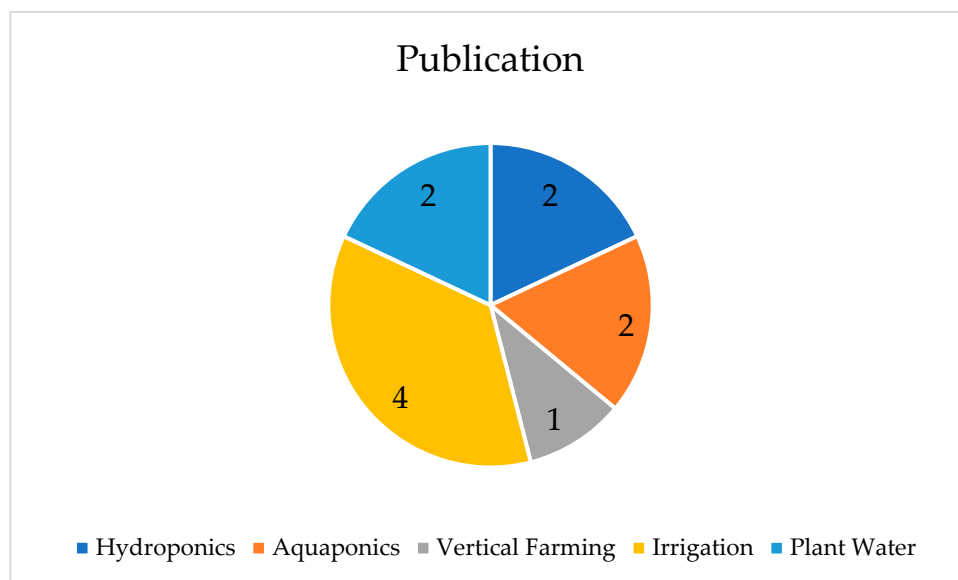


Figure 4. Breakdown of selected articles.

This distribution shows that certain areas, like irrigation, have received moderate interest in comparison to others. Irrigation scheduling using a DT optimizes water usage by creating a virtual model of agricultural systems and employing a predictive model to regulate the plant's nutrient and water requirements. Wangere et al. [73] developed and tested a real-time, automated drip irrigation system using DT technology. This DT can be integrated into existing manual irrigation setups, thereby reducing the necessity for a complete overhaul of current systems. Vertical farming, which operates in controlled environments, benefits from DTs in managing soil moisture and humidity levels [74]. Hydroponics is a soil-less method of growing plants using nutrient-rich water solutions, allowing for precise control over growth conditions. This technique often leads to faster plant growth and higher yields compared to traditional soil cultivation [75]. Effective nutrient solution, pathogen, and weed control is crucial for successful hydroponic farming. Nutrient solutions are particularly important, as productivity and yield are closely tied to nutrient consumption and pH regulation [76]. Similarly, electrical conductivity (EC) and Dissolved Oxygen (DO), which are important factors [77], can be managed by DTs. Aquaponics is a combination of aquaculture and hydroponics in a symbiotic environment [78]. Various aquaponics conditions—total dissolved solids (TDSs) in water, pH, nitrate levels, and plant growth—were modeled using simulation approaches [79]. A DT of a plant refers to a computer model that replicates the life cycle of a plant and synchronizes with the living organism under different soil, water, and weather scenarios [24]. These plant DTs leverage real-time data, mathematical and simulation models, ML algorithms, and various predictive methodologies to forecast plant behavior under diverse conditions [80]. Many studies employed process models and knowledge-based models to present a framework for developing DTs of plants [81]. Despite their efforts, these studies did not achieve predictive capabilities or effectively evaluate different scenarios.

Except for the above, DT technology has some other applications in crop modeling, such as photosynthesis, root growth simulation, water redistribution by the roots, and canopy

estimation. However, no studies have detailed the specific procedures involved in these applications. For instance, Mitsanis C et al. [82] developed a 3D model of a plant, but it lacks the incorporation of water application in the model.

4.2. DT Typology

Then, we classified the types of DTs used in these cases. According to Verdouw et al. [83], DTs can be categorized into six different types, though in practice, these features and classifications may overlap and are not always mutually exclusive. These types are described in more detail below.

Imaginary: An imaginary DT represents an object or system that has not yet been physically created. It contains all the essential information required to materialize its physical version, including functional specifications and 3D models. This type is useful for conceptualizing new designs and ideas; imaginary DTs are purely hypothetical and do not provide the data analysis capabilities or maintenance benefits of DTs based on existing physical entities [84].

Monitoring: A monitoring DT is a digital counterpart that reflects the real-time or near real-time state and behavior of a physical item. It functions to monitor the performance and environmental factors surrounding its physical counterpart [85]. This form of DT delivers insights into what is happening or has previously happened with the connected object. It also provides diagnostic insights, explaining the reasons behind these events by connecting the object with relevant contextual data. While it excels in real-time issue identification and resolution, optimizing production and reducing downtime, it does not inherently offer predictive or prescriptive insights.

Predictive: A predictive DT is a digital representation that forecasts the states and behaviors of physical things with predictive analytics, including statistical forecasting, simulations, and ML techniques. It operates dynamically, relying on real-time or near-real-time data from the physical twin. This type of DT is utilized in various industries to enable proactive maintenance and optimization [86], thereby reducing downtime and enhancing efficiency. However, it requires substantial historical data for accurate predictions and may not account for unexpected events or environmental changes [87].

Prescriptive: A prescriptive DT is an intelligent digital entity that recommends corrective and preventive actions for real-life objects using optimization algorithms and expert heuristics. It leverages the outputs from monitoring and predictive DTs to suggest actions that can achieve desired outcomes. Prescriptive DTs provide actionable insights to improve performance and enable proactive maintenance and optimization [88]. However, these recommendations require substantial historical data for accuracy and may not account for unforeseen events or environmental changes. Human decision-makers ultimately trigger and execute the recommended interventions [89].

Autonomous: An autonomous DT operates independently, fully controlling the behavior of real-life objects without human intervention. These twins can self-learn, self-diagnose, and adapt to user preferences, optimizing performance and reducing downtime. While they reduce the need for human involvement and enhance efficiency, they require substantial historical data and complex algorithms for accurate decision-making and may not account for unforeseen events or changes in the environment [90,91].

Recollection: A recollection DT maintains a comprehensive historical record of physical objects that no longer exist in real life, serving as a digital memory [92]. This type of DT captures and stores data about a physical entity for future analysis, which can help reduce environmental impacts of disposal, optimize future generations of objects, and trace product quality and safety issues. While it is valuable for analyzing past performance and optimizing

new designs, it is limited to historical data and cannot provide real-time insights, requiring sensors and other technologies for data capture.

Due to the overlapping functions of these categories, drawing clear distinctions between them proves challenging. Despite this, we tried to apply these categories to our studies to explore their practical applications in agricultural water management. The growing number of studies in recent years highlights the increasing recognition of DTs' potential to enhance agricultural efficiency and sustainability, Table 1. For aquaponics, hydroponics, and vertical farming, essential water quality parameters are pH, DO, electrical conductivity (EC), and nitrates. Additionally, humidity is a critical parameter in controlled environments. These parameters require real-time monitoring and immediate control to maintain optimal conditions for plant and fish growth. In contrast, irrigation water management encompasses not only monitoring and controlling water use but also predicting future water needs based on weather conditions. Since evapotranspiration rates increase with temperature, crop water requirements fluctuate accordingly. Therefore, effective irrigation management must consider these variations to ensure efficient water use. While the typology of DT technology presents overlapping functions, our categorization into monitoring and predictive DTs provides a useful framework for understanding and applying DTs in agricultural water management. Monitoring DTs ensure real-time control of water quality parameters, while predictive DTs allow for proactive irrigation planning, addressing the dynamic nature of crop water requirements.

Table 1. Applications, environments, and types of DTs.

Case No	Application	Environment	Type of DT	Reference	Author
1	Irrigation	Soil–water	Predictive	[93]	Alves et al.
2	Irrigation	Soil–water	Predictive	[94]	Bellvert et al.
3	Irrigation	Air–humidity	Predictive	[95]	Rahman et al.
4	Irrigation	Soil–water	Predictive	[96]	Manocha et al.
5	Plant Water	Soil–water	Predictive	[97]	Zohdi
6	Plant Water	Soil–water	Predictive	[98]	Chitu et al.
7	Vertical Farming	Soil–water Water Quality	Predictive	[99]	Batarseh et al.
8	Aquaponics	Water Quality	Predictive	[100]	Ghandar et al.
9	Aquaponics	Water Quality	Monitoring	[101]	Mahmoud et al.
10	Hydroponics	Soil–water	Monitoring	[102]	Sung et al.
11	Hydroponic	Water Quality	Predictive	[103]	Reyes Yanes et al.

The use of predictive DTs suggests a shift towards proactive management in agriculture, aiming to anticipate and address issues before they occur. In contrast, monitoring DTs are more focused on real-time data collection and immediate responses. Figure 5 shows the result of selected papers for DT types in all disciplines.

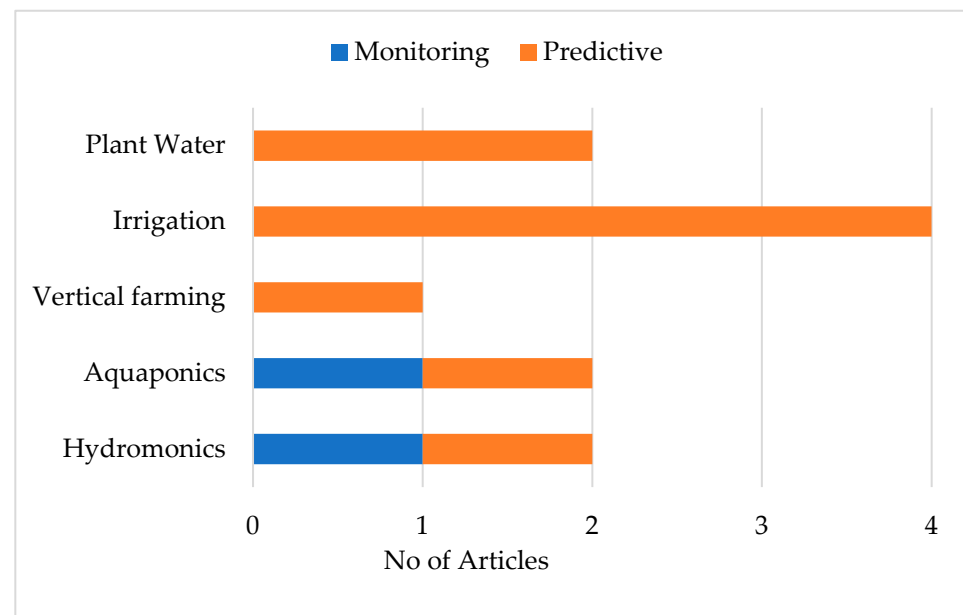


Figure 5. DT adoption: linking application areas with type of DT.

4.3. AI Integration

Agricultural growth and productivity assessments, traditionally conducted through direct observation, can now be minimized by integrating AI. ML and DL serve as simulation models. Real data are input into the prediction model, which then produces a decision. In agriculture, once the model is properly trained, validated, and verified digitally, it can offer insights on factors like soil moisture, irrigation, fertilizer recommendations, and plant growth for real-world applications. In the context of decision-making regarding irrigation requirements, the integration of advanced machine learning techniques such as the Fuzzy Inference System offers a promising approach [104]. In our review, Manocha et al. [96] use Adaptive Neuro Fuzzy Inference System (ANFIS) with a cloud computing environment. With a comparative testing accuracy of 95.85%, the ANFIS-GA model demonstrates superior precision in predicting soil conditions. This is particularly striking when compared to the standalone ANFIS model, which achieves 91.77% accuracy, alongside the Fuzzy Inference System (FIS) (89.68%) and ANN (90.86%). Its application could significantly reduce resource consumption. In another study, Alves et al. [93] use a fuzzy inference system for irrigation recommendation. The findings of their study show that the proposed system can effectively gather the necessary data to generate daily irrigation recommendations. Rehman et al. [95] introduce an automated system for plant irrigation within the greenhouse, using moisture data and their relationship with temperature to control irrigation. Among the various ML algorithms applied, including RF, SVM, and Adaptive Boosting, ANN demonstrated the highest accuracy, achieving 98%. In aquaponics, AI can be used to predict the system variables like water quality parameters, plant growth, and fish growth. Ghandhar et al. [100] develop models using LR, SVR, and CART Decision trees, in addition the ensemble method of XGB boost with decision trees. The best model for predicting plant growth was a simple linear regression.

4.4. Maturity Level

Then, we classified the use cases based on their Technology Readiness Level (TRL) to determine the maturity of DT technology in agricultural water management. The TRL scale is a framework used by the European Union to measure the maturity of a specific technology [105]. It ranges from TRL 1, where basic principles are observed, to TRL 9, where the

technology is fully integrated into operational use. This scale provides a structured pathway for evaluating technological progress, aiding in decision-making for funding and development stages and helping in identifying and mitigating risks early in the technology development process [106]. Pylianidis et al. [23] grouped these nine European Union's TRL scales further into three broad categories, conceptual, prototype, and deployed phase, as shown in Table 2, to address the maturity level of technology.

Table 2. Technology Readiness Level (TRL) scale.

TRL No	Technology Readiness Level Description	Maturity
1	Basic principles observed	Conceptual Phase
2	Technology concept formulated	
3	Experimental proof of concept	
4	Technology validated in lab	Prototype Phase
5	Technology validated in relevant environment	
6	Technology demonstrated in relevant environment	
7	System prototype demonstration in operational environment	Deployed Phase
8	System complete and qualified	
9	Actual system proven in operational environment	

The integration of IoT and remote sensing techniques is essential for developing DTs in agriculture, providing necessary data for accurate digital models. Key sensors include pH, electrical conductivity (EC), nitrate, and turbidity sensors for aquaponics and hydroponics, as well as humidity and light intensity sensors for vertical farming. Soil moisture sensors and remote sensing are crucial for irrigation, while flow meters and pressure sensors are used across all applications to control water flow.

Table 3 shows that most DT technologies for agriculture water are still in the conceptual and prototype phases, which indicates the complex relationship between plants, soil, the environment, and water requirements.

Table 3. AI integration and DT maturity level.

Case No	Application	AI Integration	DT Maturity Level	Technology Used	Reference	Author
1	Irrigation	Fuzzy Inference algorithm used to determine irrigation recommendation	Prototype	IoT Sensors, actuators, FIWARE IoT platform, plant simulation using SQL database, Programmable Logic Controller (PLC), Open Platform Communications Unified Architecture (OPC UA) servers, Sprinkles, Grafana for data analysis, OPC UA server to simulate irrigation system	[93]	Alves et al.
2	Irrigation	ML used to measure land surface temperature	Prototype	Soil moisture sensor, irrigation decision support system (DSS) using soil water balance simulations, satellite images using Sentinel, fraction of intercepted photosynthetically active radiation (fIPAR)	[94]	Bellvert et al.

Table 3. Cont.

Case No	Application	AI Integration	DT Maturity Level	Technology Used	Reference	Author
3	Irrigation	Artificial Neural Networks (ANNs), Random Forest (RF), Support Vector Machine (SVM), and Adaptive Boosting used for irrigation management	Prototype	Sensors (temp, moisture,), IBM Watson as IoT platform	[95]	Rahman et al.
4	Irrigation	Adaptive Neuro-Fuzzy Inference System (ANFIS) used to calculate irrigation requirement	Prototype	IoT, thermal imaging for evapotranspiration, Ubidots as IoT platform	[96]	Manocha et al.
5	Plant Water	Genetic Algorithms (GAs)	Prototype	Satellite images, LiDAR, physics engine	[97]	Zohdi
6	Plant Water	No Information	Prototype	Satellite images, sensors (soil, moisture)	[98]	Chitu et al.
7	Vertical farming	AI used but no mention of any specific technique	Prototype	Sensors (pH, temp, EC, water level, water flow, nitrate, turbidity, soil probes), cyber-physical system, ACWA simulator	[99]	Batareseh et al.
8	Aquaponics	Linear regression (LR), Support Vector Regression (SVR), XGB, CART decision trees models used to determine system variables	Prototype	Sensors (temp, DO, pH, light intensity, EC,0), IoT platform, cyber-physical system, Dynamic Data-Driven Application System (DDDAS)	[100]	Ghandar et al.
9	Aquaponics	No information about ML	Prototype	Sensors (PH, temp, DO, light, pumps, and actuators), Raspberry pi as IoT platform, Firebase	[101]	Mahmoud et al.
10	Hydroponics	No information about ML	Prototype	Sensors (temp, DO, pH, light intensity, EC), big data analytics, cyber-physical system, Secure Multi-Crop Smart Irrigation System (SMCSIS)	[102]	Sung et al.
11	Hydroponics	DL is used to estimate growth rate and weight of plants	Prototype	Sensors (temp, DO, pH, light intensity, EC,), CropKing [®] NFT Desktop System, Raspberry pi as IoT platform.	[103]	Reyes Yanes et al.

4.5. Key Concept and Applications

Implementing DT technologies in agricultural water management offers significant benefits across irrigation, hydroponics, aquaponics, and plant and vertical farming.

4.5.1. Digital Twins in Irrigation

Alves et al. [93] designed a DT for managing irrigation in smart farming with a focus on water conservation. The system integrates a FIWARE-based IoT platform with a discrete event simulation model powered by Siemens Plant Simulation software. It collects and processes data related to soil, weather, and crops to generate daily irrigation recommendations. A Fuzzy Inference System, a form of rule-based AI, was employed to generate irrigation

recommendations based on environmental data. The DT enables a continuous real-time exchange of data between physical elements, such as sensors and actuators, and their digital models. This method aims to increase water use efficiency, optimize irrigation practices, and allow for the testing of various irrigation strategies before they are implemented in the field.

Bellvert et al. [94] developed a DT system for automated irrigation scheduling in a commercial vineyard utilizing Sentinel-2 biophysical variables. The study validated the use of near real-time fAPAR data to optimize irrigation through regulated deficit irrigation (RDI) strategies. This DT integrated soil moisture sensors, weather data, and remote sensing inputs to determine precise irrigation requirements. The findings indicated strong correlations between fAPAR and in situ measurements, enabling efficient water management. The system allowed for adaptive responses to changing conditions, ensuring optimal water usage and enhancing vine stress management during various growth stages.

Rahman H et al. [95] developed a DT framework for managing smart greenhouses, utilizing next-generation mobile networks and ML. This system employs the IBM Watson platform for IoT operations. They developed ML algorithms for predictive analytics and decision-making, enabling the activation of irrigation systems based on humidity levels and the regulation of internal greenhouse temperatures. Notable advancements include the deployment of 5G networks for uninterrupted data transmission and the capacity for expansion through commercial cloud technologies.

Manocha et al. [96] proposed a smart irrigation framework utilizing DTs, IoT, and AI to address water usage inefficiencies in agriculture. The framework integrates physical sensors and actuators with virtual counterparts to create a DT that simulates the irrigation system's behavior. The goal of this system is to enhance decision-making and water conservation by processing data collected from IoT devices to determine daily irrigation needs. Key benefits include evaluating system performance before field implementation and comparing various irrigation methods, ultimately improving farm operations and reducing water consumption by providing real-time information on soil, weather, and crops.

4.5.2. Digital Twins in Plant Water

Zohdi [97] developed a ML-based DT framework to optimize agriculture biomass at large scales. It integrates real-world data from LiDAR and multispectral sensors with simulations to create digital replicas of agricultural systems. This DT optimizes key variables like plant density, water availability, light intensity, and soil quality, etc., to predict the biomass. A physics engine models plant growth, while Genetic Algorithms solve complex optimization problems. The framework is scalable, supporting small farms to large plantations.

Chitu et al. [98] developed a DT model to simulate and optimize corn, wheat, and rapeseed yields using real-time data from IoT sensors, satellite imagery, and previous records. The model integrates key variables like soil moisture, rainfall, irrigation, temperature, nutrient levels, and climatic factors to adapt farming practices, including seeding and fertilization. It highlights the importance of water and nitrogen management in improving yields. It supports predictive analytics for resource optimization, offering a sustainable solution for precision agriculture.

4.5.3. Digital Twins in Vertical Farming

Batarseh et al. [99] introduced the ACWA (AI and Cyber for Water and Agriculture) testbed, an advanced system addressing challenges in water resource management and agriculture, including vertical farming water and soil relationships. Integrating AI, ACWA facilitates innovative experimentation. The testbed features modular topologies, sensors, computational clusters, pumps, tanks, and smart water devices, enabling dynamic simulations of water distribution and soil scenarios. It generates datasets for AI model development,

water quality analysis, and leakage detection. With high-frequency data collection, ACWA supports detailed analysis and data-driven decision-making, offering an open-access repository to foster collaboration and advancements in sustainable practice.

4.5.4. Digital Twins in Aquaponics

Ghandar et al. [100] described a decision support system for urban agriculture that utilizes a DT framework and ML to optimize aquaponics. The system employs sensors for monitoring parameters such as water quality, including pH and turbidity, and other critical variables like DO, temperature, and TDS. The paradigm of a Dynamic Data-Driven Application System (DDDAS) is implemented, with data processed through a Raspberry Pi. The simulation operates as a series of modules, covering aspects such as fish feed, TDS, fish weight gain, pH, nitrates, and plant growth, ensuring a comprehensive and integrated approach to managing urban agriculture systems.

Mahmoud et al. [101] introduced an economic smart aquaponic system leveraging IoT and DT technologies to enhance sustainability and efficiency in aquaculture and hydroponics. The system integrates physical sensors for the continuous monitoring of key parameters, including pH, temperature, water level, DO, and sunlight intensity, managed by a Raspberry Pi. Data are synchronized in real-time using the Firebase platform, facilitating remote supervision and control via IoT. The system prioritizes water quality over irrigation requirements, aiming to reduce labor costs and enhance productivity. This approach simplifies operation, improves resource management, and lowers human intervention by approximately 70%.

4.5.5. Digital Twins in Hydroponics

Sung et al. [102] explored the implementation of DT technology in agriculture. The study presents a DT architecture for smart farms, detailing its application at both laboratory and field levels. The design of the smart farm is comprehensive, incorporating ICT, IoT, big data analytics, and smart equipment to enhance productivity and efficiency. A notable component is the Secure Multi-Crop Smart Irrigation System (SMCSIS), which, while focused on irrigation, exemplifies the broader applicability of DT in smart farming. The paper also discusses future research directions for expanding DT applications in various agricultural domains.

Reyes yanes et al. [103] presented a comprehensive framework for developing a DT of hydroponic grow beds in intelligent aquaponic systems. The framework integrates IoT technology, databases, centralized control, and a virtual interface, enabling real-time monitoring of key parameters such as pH, electroconductivity, water temperature, relative humidity, air temperature, and light intensity. The DT supports the use of techniques to predict crop growth rate and fresh weight, offering a robust platform for optimizing aquaponic crop yields and reducing labor costs by providing real-time feedback and control.

To our knowledge, this research study represents the first systematic literature review (SLR) on water management in agriculture using DTs. We identified 48 papers and selected 11 high-quality primary studies for detailed analysis. Most of these studies have been identified through the Web of Science database.

4.6. Limitation of Search

There are some limitations that may have affected our literature review. Our query string exclusively on the term ‘digital twin’, excluding aliases such as AI, ML, DL simulation, CPS, DSS, IoT, Digital Model, and other similar terms. AI has long been utilized in smart farming and precision agriculture. Simulations have been employed for water quality and crop irrigation for many years [107]. However, the emergence of the term ‘digital twin’ (DT) marks a significant advancement in this field. DTs mostly utilize AI, simulations, CPS, and

the IoT to create dynamic models of physical agricultural systems, but not all simulation models and IoT systems qualify as DTs.

To limit the articles and focus on our objective, we ensured that the term ‘digital twin’ appeared at least once in the title, abstract, and keywords of the selected studies. There may be some other articles on DT technology in agriculture water management, but it is unlikely that an article would omit the term ‘digital twin’ from the title, abstract, and keywords. We searched for articles in all well-known databases. While it is possible that additional articles exist in other databases, we believe that if well-known databases contain limited papers on this topic, other databases are likely to have even fewer. Therefore, we think finding additional papers elsewhere will not significantly affect our review. Additionally, PRISMA guidelines do not impose a minimum number of articles for a systematic review.

5. Discussion

The reviewed literature highlights the growing adoption of DT technology in agriculture, particularly in water management. DTs have demonstrated their potential to address critical challenges related to water scarcity, sustainability, and efficiency. In irrigation, DTs are employed to monitor soil moisture, evapotranspiration, and predict irrigation water requirements by integrating ML, models, AI, IoT sensor data, remote sensing data, and decision support models [108]. These technologies also facilitate the management of plant water availability, which impacts growth and productivity through inputs such as rainfall, irrigation, and soil moisture [109].

DT applications extend beyond traditional irrigation systems to advanced setups such as hydroponics and aquaponics, where they maintain water quality by continuously monitoring parameters like pH, nutrient concentration, and temperature. This ensures the health and productivity of both plants and fish, preventing potential issues through real-time adjustments. The analysis indicates that DTs are primarily used for predictive purposes, focusing on soil–water interactions and water quality management. Based on the review, DT applications can be categorized into monitoring DTs and predictive DTs. Monitoring DTs emphasize real-time data collection and immediate response to changes in water quality and environmental conditions, crucial for systems like aquaponics, hydroponics, and vertical farming. Predictive DTs, on the other hand, forecast future water requirements by integrating weather data and other environmental variables, enabling proactive irrigation management to optimize water use and improve crop yields.

Several tools and platforms were identified as integral to DT systems. MongoDB, a NoSQL database, is particularly effective in handling large volumes of unstructured data generated by IoT devices and remote sensing systems, ensuring scalability and efficiency in data storage [110]. Node-RED, a flow-based development tool, integrates IoT devices, streamlining the collection and processing of sensor data for real-time decision-making in DT systems [111]. R Dashboards enable real-time visualization of system performance, providing actionable insights to enhance water management and system efficiency [112]. Python, due to its extensive libraries such as Pandas, NumPy, and Scikit-learn, supports AI development by enabling data analysis, model building, and automation tasks [113]. TensorFlow and Keras simplify the creation and training of deep learning models, allowing for advanced predictive analytics [114], such as forecasting irrigation needs or simulating crop growth scenarios under different environmental conditions.

Raspberry Pi, Ubidots, and FIWARE aggregate sensor data, feeding them into DT systems for real-time monitoring and predictive analytics. Despite their potential, most studies remain at the prototype stage, with only a few implemented in actual field conditions. This highlights significant challenges, including the complexity and variability of agricul-

tural environments, the need for reliable high-resolution data, and the integration of diverse sensor types.

DT technologies also provide substantial benefits across various agricultural practices. These include real-time monitoring and control of water usage, predictive maintenance to minimize downtime, resource optimization in water-scarce areas, and enhanced decision-making based on comprehensive data. Additionally, DTs contribute to cost savings through optimized water use and reduced maintenance expenses while promoting sustainability by minimizing water waste and environmental impact. Their versatility allows customization and scalability across different agricultural setups. Moreover, DT technology has been applied in several agriculture-related areas, including crop production [115], livestock management [116], and farm robotics [117]. In crop production, DTs support monitoring, resource optimization and decision-making for cultivation practices. In livestock, they enable real-time monitoring and management of animal health and performance. In farm machinery and water pumps, DTs help monitor equipment status, predict maintenance needs, and improve operational efficiency. These applications demonstrate the growing potential of DT in modernizing various aspects of agriculture.

Overall, DT technologies enable more efficient, sustainable, and productive agricultural practices by leveraging real-time data and simulations to optimize water management.

5.1. Practical Impact of DTs on Water Management

DT technology is rapidly changing how farmers manage water, helping them make smarter, clearer decisions based on real-time data. By creating digital copies of actual farms, DT allows farmers to see exactly what's happening in their fields without guesswork. Instead of relying on traditional methods, which often involve trial and error, farmers can now use these virtual models to apply water precisely where and when it is needed. This helps conserve water, cuts unnecessary costs, and ultimately improves the health and productivity of crops. One key benefit of DTs is their ability to test different scenarios virtually. For example, farmers can simulate how their crops might react to drought, heavy rainfall, or sudden changes in weather. This means they can explore different strategies safely, without risking their real crops. Such preparation helps reduce risks and makes farms more resilient to unpredictable climate conditions. Additionally, DTs can quickly identify early signs of stress in plants or changes in water quality. Early detection gives farmers a chance to act promptly and avoid losses or damage. Another important advantage is that DT technology is flexible enough to work well for both large-scale farms and smaller family-owned farms. On bigger farms, DTs help manage complex irrigation networks more efficiently, keeping costs down and productivity high. For small-scale farmers, DTs offer affordable tools to use limited resources wisely, helping them stay competitive and sustainable.

Overall, DT technology offers farmers practical and effective ways to handle modern challenges like water shortages, rising costs, and uncertain weather patterns. By making better-informed decisions, farmers can use their resources efficiently, reduce risks and achieve higher profitability, creating stronger, healthier, and more sustainable farming operations.

5.2. Scalability

One critical aspect of adopting DTs in agriculture, especially in areas like irrigation, hydroponics, aquaponics, and vertical farming, is their scalability and the ease with which these systems can grow from small experimental setups to larger farms. For instance, smaller farms often face a significant digital divide, where limited financial resources and technical know-how make adopting advanced DT systems challenging, while platforms using open and flexible standards (such as FIWARE-based frameworks and OPC UA communication protocols) are designed explicitly for scalability.

In aquaponics, DT systems built around IoT technologies are indeed scalable because they simplify operations and reduce the need for highly specialized skills. Yet, even with these advantages, managing biological systems where fish and plants closely interact remains complex. This complexity requires significant technical knowledge, which can slow down or limit widespread adoption. Similarly, DT frameworks proposed for vertical and smart farming aim to help farmers better manage resources without needing constant on-site presence or specialized training.

Finally, IoT-based DT frameworks intended for irrigation management are described as highly adaptable across different scales, from small-scale farms to larger agricultural operations. This adaptability is especially important in arid regions, where scalable, cost-effective solutions are crucial to addressing limited water resources and dense agricultural practices.

5.3. Practical Barriers

While DTs present significant potential for agricultural applications, several implementation barriers must be addressed. A primary challenge involves the requirement for specialized technical expertise and sustained support systems. The sophisticated nature of these systems, which integrate advanced sensors, machinery, and digital platforms, requires reliable access to technical specialists. This requirement poses particular difficulties for small-scale operations, consistent with historical patterns of slower digital adoption in agriculture sectors.

Data integration presents another substantial obstacle. Combining heterogeneous data streams from soil sensors, meteorological stations, remote sensing platforms, and historical production records into a unified DT framework requires skills and expertise. The availability of high-speed internet is still a problem in remote areas [118]. Each data source demands specific processing protocols and interpretive methodologies, complicating both initial implementation and ongoing system maintenance. Environmental variability is another uncertainty in predictive models.

Another major barrier is the need for physical infrastructure. Setting up sensor networks across large agricultural areas requires a high upfront investment and careful planning for proper installation and coverage. The continuous maintenance of monitoring equipment and data transmission systems and a reliable algorithm [119] are essential for ensuring data reliability. These substantial resource requirements may deter adoption without clear demonstrations of system efficacy through robust pilot testing and simulation validation.

5.4. Economic Viability

The economic feasibility of DTs significantly influences their agricultural implementation. Their adoption faces substantial financial barriers, particularly for small-scale operations. Initial investments in sensor networks, drones, and data infrastructure create notable entry barriers, compounded by ongoing maintenance and technical support costs.

Aquaponic systems illustrate these challenges well, as their high equipment costs and labor expenditures, frequently reaching 50% of operational budgets, limit adoption. However, the study by Ghandar A et al. [100] demonstrates that DT automation can reduce labor costs by up to 70%, with IoT integration showing significant operational savings. Irrigation systems similarly achieve improved cost-effectiveness through DT approaches.

The technology's long-term economic potential is clear, but widespread adoption requires overcoming initial cost barriers and demonstrating tangible financial benefits across different farm scales. This necessitates strategic implementation planning and scalable solutions tailored to varying operational capacities.

6. Conclusions

In conclusion, our SLR emphasizes the trend and potential of DTs in the domain of agriculture water management. As the agricultural sector increasingly recognizes the importance of sustainable water use, DTs emerge as a promising tool, yet their adoption is still in nascent stages. The complexity and heterogeneity of agricultural environments present significant challenges to the widespread implementation of DT technology. The current applications of DTs in agriculture water primarily include irrigation, hydroponics, aquaponics, and vertical farming. These applications are predominantly in their initial phases, often confined to prototype stages. The majority of data acquisition for these DT systems is facilitated through AI, ML algorithms, IoT technologies, and remote sensing, which enable real-time data collection, monitoring, and prediction.

The types of DTs, both with and without AI technologies, discussed in the reviewed studies primarily focus on monitoring and predictive capabilities. These enable the precise monitoring of water quality in hydroponics and aquaponics systems and the prediction of irrigation needs.

Future Perspective

Virtual models utilizing real-time and continuous data about agricultural assets can predict and resolve hidden problems in the field. DTs offer solutions to minimize weather-related risks by providing real-time forecasting and predictive simulations. By integrating data from satellites, weather stations, and IoT-enabled field sensors, DT models generate highly accurate weather predictions, allowing farmers to optimize planting, irrigation, and harvesting schedules. For instance, a study by Kim and Heo [56] demonstrated the successful application of a DT system in an open-field mandarin orchard, where predictive analytics helped farmers mitigate weather-induced hazards, optimize resource allocation, and significantly reduce crop losses. Similar approaches have been employed in the context of agricultural machinery. A recent study conducted by Yin Y et al. [120] has demonstrated the effective development of a DT specifically designed for combine harvesters. This system integrates detailed modeling of component motions, real-time sensor data collection, and predictive analytics, significantly enhancing operational efficiency and accuracy in harvesting tasks. However, there is a noticeable absence of comparative studies between traditional CPSs and those integrated with AI and DTs, which could provide valuable insights into the relative advantages and drawbacks of these approaches. Future research needs to address critical aspects such as the quantifiable savings in water usage, its integration with climate models, the efficiency of the system, the economic feasibility of DT implementation, and its impact on agricultural yield. Works on these aspects will directly address the application of DT in agriculture water management. To realize its full potential, further research and development are necessary, focusing on practical applications, economic assessments, and collaborative efforts to bridge the gap between theoretical concepts and real-world implementation.

Funding: This research received no external funding.

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

References

1. Hemond, O.; Butsic, V.; Moanga, D.; Wartenberg, A.C. Farm consolidation and turnover dynamics linked to increased crop diversity and higher agricultural input use. *Agric. Syst.* **2023**, *210*, 103708. [[CrossRef](#)]
2. Yang, M.; Zhu, Y.; Zhao, Y.; Li, C.; Zhang, Y.; Fan, Y.; Yang, W.; Kang, M. Life cycle water and energy consumption and efficiency analysis of major crops in China. *J. Clean. Prod.* **2024**, *467*, 142899. [[CrossRef](#)]

3. Water Scarcity, the Climate Crisis and Global Food Security: A Call for Collaborative Action 2023. 2023. Available online: <https://www.un.org/en/un-chronicle/water-scarcity-climate-crisis-and-global-food-security-call-collaborative-action> (accessed on 17 July 2024).
4. Wang, J.; Xue, L.; Liu, H.; Cao, B.; Bai, Y.; Xiang, C.; Li, X. Patterns of salt transport and factors affecting typical shrub in desert-oases transition areas. *Environ. Res.* **2023**, *236*, 116804. [[CrossRef](#)] [[PubMed](#)]
5. Singh, A. Effective Management of Water Resources Problems in Irrigated Agriculture Through Simulation Modeling. *Water Resour. Manag.* **2024**, *38*, 2869–2887. [[CrossRef](#)]
6. Abioye, E.A.; Abidin, M.S.Z.; Mahmud, M.S.A.; Buyamin, S.; Ishak, M.H.I.; Rahman, M.K.I.A.; Otuoze, A.O.; Onotu, P. A review on monitoring and advanced control strategies for precision irrigation. *Comput. Electron. Agric.* **2020**, *173*, 105441. [[CrossRef](#)]
7. Anjum, M.N.; Cheema, M.J.M.; Hussain, F.; Wu, R.-S. Chapter 6—Precision irrigation: Challenges and opportunities. In *Precis Agric*; Zaman, Q., Ed.; Academic Press: Cambridge, MA, USA, 2023; pp. 85–101. [[CrossRef](#)]
8. Rodríguez-Pérez, A.M.; Rodríguez-Gonzalez, C.A.; López, R.; Hernández-Torres, J.A.; Caparrós-Mancera, J.J. Water Microturbines for Sustainable Applications: Optimization Analysis and Experimental Validation. *Water Resour. Manag.* **2024**, *38*, 1011–1025. [[CrossRef](#)]
9. Javaid, M.; Haleem, A.; Khan, I.H.; Suman, R. Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Adv. Agrochem.* **2023**, *2*, 15–30. [[CrossRef](#)]
10. Sheikh, M.; Iqra, F.; Ambreen, H.; Pravin, K.A.; Ikra, M.; Chung, Y.S. Integrating artificial intelligence and high-throughput phenotyping for crop improvement. *J. Integr. Agric.* **2024**, *23*, 1787–1802. [[CrossRef](#)]
11. Pace, R.; Di Cola, V.S.; Monti, M.M.; Affinito, A.; Cuomo, S.; Loreto, F.; Ruocco, M. Artificial intelligence in soil microbiome analysis: A potential application in predicting and enhancing soil health—A review. *Discov. Appl. Sci.* **2025**, *7*, 85. [[CrossRef](#)]
12. Padhiary, M.; Saha, D.; Kumar, R.; Sethi, L.N.; Kumar, A. Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agric. Technol.* **2024**, *8*, 100483. [[CrossRef](#)]
13. Novielli, P.; Romano, D.; Pavan, S.; Losciale, P.; Stellacci, A.M.; Diacono, D.; Bellotti, R.; Tangaro, S. Explainable artificial intelligence for genotype-to-phenotype prediction in plant breeding: A case study with a dataset from an almond germplasm collection. *Front. Plant Sci.* **2024**, *15*, 1434229. [[CrossRef](#)]
14. Novielli, P.; Magarelli, M.; Romano, D.; de Trizio, L.; Di Bitonto, P.; Monaco, A.; Amoroso, N.; Stellacci, A.M.; Zoani, C.; Bellotti, R.; et al. Climate Change and Soil Health: Explainable Artificial Intelligence Reveals Microbiome Response to Warming. *Mach. Learn. Knowl. Extr.* **2024**, *6*, 1564–1578. [[CrossRef](#)]
15. Raouhi, E.M.; Zouizza, M.; Lachgar, M.; Zouani, Y.; Hrimech, H.; Kartit, A. AIDSII: An AI-based digital system for intelligent irrigation. *Softw. Impacts* **2023**, *17*, 100574. [[CrossRef](#)]
16. Navarro, E.; Costa, N.; Pereira, A. A systematic review of IoT solutions for smart farming. *Sensors* **2020**, *20*, 4231. [[CrossRef](#)]
17. Wang, L. Digital Twins in Agriculture: A Review of Recent Progress and Open Issues. *Electronics* **2024**, *13*, 2209. [[CrossRef](#)]
18. Abbasi, R.; Martinez, P.; Ahmad, R. The digitization of agricultural industry—A systematic literature review on agriculture 4.0. *Smart Agric. Technol.* **2022**, *2*, 100042. [[CrossRef](#)]
19. Peladarinos, N.; Piromalis, D.; Cheimaras, V.; Tserepas, E.; Munteanu, R.A.; Papageorgas, P. Enhancing Smart Agriculture by Implementing Digital Twins: A Comprehensive Review. *Sensors* **2023**, *23*, 7128. [[CrossRef](#)]
20. Pandey, D.K.; Mishra, R. Towards sustainable agriculture: Harnessing AI for global food security. *Artif. Intell. Agric.* **2024**, *12*, 72–84. [[CrossRef](#)]
21. Nasirahmadi, A.; Hensel, O. Toward the Next Generation of Digitalization in Agriculture Based on Digital Twin Paradigm. *Sensors* **2022**, *22*, 498. [[CrossRef](#)]
22. Cesco, S.; Sambo, P.; Borin, M.; Basso, B.; Orzes, G.; Mazzetto, F. Smart agriculture and digital twins: Applications and challenges in a vision of sustainability. *Eur. J. Agron.* **2023**, *146*, 126809. [[CrossRef](#)]
23. Pylianidis, C.; Osinga, S.; Athanasiadis, I.N. Introducing digital twins to agriculture. *Comput. Electron. Agric.* **2021**, *184*, 105942. [[CrossRef](#)]
24. Dawn, N.; Ghosh, S.; Saha, A.; Chatterjee, S.; Ghosh, T.; Guha, S.; Sarkar, S.; Mukherjee, P.; Sanyal, T. A Review on Digital Twins Technology: A New Frontier in Agriculture. *Artif. Intell. Appl.* **2023**, *2*, 250–262. [[CrossRef](#)]
25. Escribà-Gelonch, M.; Liang, S.; van Schalkwyk, P.; Fisk, I.; Long, N.V.D.; Hessel, V. Digital Twins in Agriculture: Orchestration and Applications. *J. Agric. Food Chem.* **2024**, *72*, 10737–10752. [[CrossRef](#)] [[PubMed](#)]
26. Purcell, W.; Neubauer, T.; Mallinger, K. Digital Twins in agriculture: Challenges and opportunities for environmental sustainability. *Curr. Opin. Env. Sustain.* **2023**, *61*, 101252. [[CrossRef](#)]
27. Tagarakis, A.C.; Benos, L.; Kyriakarakos, G.; Pearson, S.; Sørensen, C.G.; Bochtis, D. Digital Twins in Agriculture and Forestry: A Review. *Sensors* **2024**, *24*, 3117. [[CrossRef](#)] [[PubMed](#)]
28. Liu, J.; Zhou, Y.; Li, Y.; Li, Y.; Hong, S.; Li, Q.; Liu, X.; Lu, M.; Wang, X. Exploring the Integration of Digital Twin and Generative AI in Agriculture. In Proceedings of the 2023 15th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, China, 26–27 August 2023; pp. 223–228. [[CrossRef](#)]

29. Olawade, D.B.; Wada, O.Z.; Ige, A.O.; Egbewole, B.I.; Olojo, A.; Oladapo, B.I. Artificial intelligence in environmental monitoring: Advancements, challenges, and future directions. *Hyg. Environ. Health Adv.* **2024**, *12*, 100114. [CrossRef]
30. Mana, A.A.; Allouhi, A.; Hamrani, A.; Rehman, S.; El Jamaoui, I.; Jayachandran, K. Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices. *Smart Agric. Technol.* **2024**, *7*, 100416. [CrossRef]
31. Riaz, K.; McAfee, M.; Gharbia, S.S. Management of Climate Resilience: Exploring the Potential of Digital Twin Technology, 3D City Modelling, and Early Warning Systems. *Sensors* **2023**, *23*, 2659. [CrossRef]
32. Rajmis, S.; Karpinski, I.; Pohl, J.-P.; Herrmann, M.; Kehlenbeck, H. Economic potential of site-specific pesticide application scenarios with direct injection and automatic application assistant in northern Germany. *Precis. Agric.* **2022**, *23*, 2063–2088. [CrossRef]
33. Singh, G.; Rajesh, R.; Daultani, Y.; Misra, S.C. Resilience and sustainability enhancements in food supply chains using Digital Twin technology: A grey causal modelling (GCM) approach. *Comput. Ind. Eng.* **2023**, *179*, 109172. [CrossRef]
34. Yadav, M.; Vashisht, B.; Vullaganti, N.; Kumar, P.; Jalota, S.; Kumar, A.; Kaushik, P. UAV-enabled approaches for irrigation scheduling and water body characterization. *Agric. Water Manag.* **2024**, *304*, 109091. [CrossRef]
35. Liu, P.; Li, J.; Wang, L.; He, G. Remote Sensing Data Fusion With Generative Adversarial Networks: State-of-the-art methods and future research directions. *IEEE Geosci. Remote Sens. Mag.* **2022**, *10*, 295–328. [CrossRef]
36. Cui, Y.; Li, Y.; Tang, H.; Turowski, J.M.; Yan, Y.; Bazai, N.A.; Wei, R.; Li, L. A digital-twin platform for cryospheric disaster warning. *Natl. Sci. Rev.* **2024**, *11*, nwae300. [CrossRef] [PubMed]
37. Brocca, L.; Barbeta, S.; Camici, S.; Ciabatta, L.; Dari, J.; Filippucci, P.; Massari, C.; Modanesi, S.; Tarpanelli, A.; Bonaccorsi, B.; et al. A Digital Twin of the terrestrial water cycle: A glimpse into the future through high-resolution Earth observations. *Front. Sci.* **2024**, *1*, 1190191. [CrossRef]
38. Chen, H.; Xiao, X.; Chen, C.; Chen, M.; Li, C.; Lu, K.; Lin, H.; Fang, C. Digital twin-based virtual modeling of the Poyang Lake wetland landscapes. *Environ. Model. Softw.* **2024**, *181*, 106168. [CrossRef]
39. Grieves, M. Digital Twin: Manufacturing Excellence through Virtual Factory Replication. Available online: https://www.researchgate.net/publication/275211047_Digital_Twin_Manufacturing_Excellence_through_Virtual_Factory_Replication (accessed on 18 July 2024).
40. Stark, R.; Kind, S.; Neumeyer, S. Innovations in digital modelling for next generation manufacturing system design. *CIRP Ann. Manuf. Technol.* **2017**, *66*, 169–172. [CrossRef]
41. Tao, F.; Zhang, M.; Liu, Y.; Nee, A.Y.C. Digital twin driven prognostics and health management for complex equipment. *CIRP Ann.* **2018**, *67*, 169–172. [CrossRef]
42. Ponomarev, K.; Kudryashov, N.; Popelnukha, N.; Potekhin, V. Main principals and issues of digital twin development for complex technological processes. In Proceedings of the International DAAAM Symposium on Intelligent Manufacturing and Automation, Zadar, Croatia, 8–11 November 2017; pp. 523–528. [CrossRef]
43. Redelinghuys, A.; Basson, A.; Kruger, K. A Six-Layer Digital Twin Architecture for a Manufacturing Cell. In *Service Orientation in Holonic and Multi-Agent Manufacturing*; Borangiu, T., Trentesaux, D., Thomas, A., Cavalieri, S., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 412–423.
44. 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]
45. Semeraro, C.; Lezoche, M.; Panetto, H.; Dassisti, M. Digital twin paradigm: A systematic literature review. *Comput. Ind.* **2021**, *130*, 103469. [CrossRef]
46. Chang, V.; Sharma, S.; Li, C.S. Smart cities in the 21st century. *Technol. Forecast. Soc. Change* **2020**, *153*, 119447. [CrossRef]
47. Zimit, A.Y.; Jibril, M.M.; Azimi, M.S.; Abba, S.I. Hybrid predictive based control of precipitation in a water-scarce region: A focus on the application of intelligent learning for green irrigation in agriculture sector. *J. Saudi Soc. Agric. Sci.* **2023**, *22*, 524–534. [CrossRef]
48. Touil, S.; Richa, A.; Fizir, M.; Argente García, J.E.; Skarmeta Gómez, A.F. A review on smart irrigation management strategies and their effect on water savings and crop yield. *Irrig. Drain.* **2022**, *71*, 1396–1416. [CrossRef]
49. Bwambale, E.; Abagale, F.K. Smart Irrigation Monitoring and Control. In *Encyclopedia of Smart Agriculture Technologies*; Zhang, Q., Ed.; Springer International Publishing: Cham, Switzerland, 2022; pp. 1–7. [CrossRef]
50. Tao, F.; Zhang, H.; Liu, A.; Nee, A.Y.C. Digital Twin in Industry: State-of-the-Art. *IEEE Trans. Ind. Inf.* **2019**, *15*, 2405–2415. [CrossRef]
51. Oks, S.J.; Jalowski, M.; Lechner, M.; Mirschberger, S.; Merklein, M.; Vogel-Heuser, B.; Möslin, K.M. Cyber-Physical Systems in the Context of Industry 4.0: A Review, Categorization and Outlook. *Inf. Syst. Front.* **2022**, *26*, 1731–1772. [CrossRef]
52. Janani, N.; Kannan, B.; Nagarajan, K.; Thiagarajan, G.; Duraisamy, M.R. Soil moisture mapping for different land-use patterns of lower Bhavani river basin using vegetative index and land surface temperature. *Env. Dev. Sustain.* **2024**, *26*, 4533–4549. [CrossRef]
53. Arafa, Y.; El-Gindy, A.-G.M.; El-Shirbeny, M.; Bourouah, M.; Abd-ElGawad, A.M.; Rashad, Y.M.; Hafez, M.; Youssef, M.A. Improving the spatial deployment of the soil moisture sensors in smart irrigation systems using GIS. *Cogent Food Agric.* **2024**, *10*, 2361124. [CrossRef]

54. Tsai, P.H.; Huang, Y.; Tai, J.H. Estimating soil water content from thermal images with an artificial neural network. *Catena* **2024**, *241*, 108029. [\[CrossRef\]](#)
55. Sciullo, L.; De Marchi, A.; Trotta, A.; Montori, F.; Bononi, L.; Di Felice, M. Relativistic Digital Twin: Bringing the IoT to the future. *Future Gener. Comput. Syst.* **2024**, *153*, 521–536. [\[CrossRef\]](#)
56. Kim, S.; Heo, S. An agricultural digital twin for mandarins demonstrates the potential for individualized agriculture. *Nat. Commun.* **2024**, *15*, 1561. [\[CrossRef\]](#)
57. Sorri, K.; Mustafee, N.; Seppänen, M. Revisiting IoT definitions: A framework towards comprehensive use. *Technol. Forecast. Soc. Change* **2022**, *179*, 121623. [\[CrossRef\]](#)
58. Rejeb, A.; Rejeb, K.; Abdollahi, A.; Al-Turjman, F.; Treiblmaier, H. The Interplay between the Internet of Things and agriculture: A bibliometric analysis and research agenda. *Internet Things* **2022**, *19*, 100580. [\[CrossRef\]](#)
59. Xu, J.; Gu, B.; Tian, G. Review of agricultural IoT technology. *Artif. Intell. Agric.* **2022**, *6*, 10–22. [\[CrossRef\]](#)
60. Zappa, L.; Schlaffer, S.; Brocca, L.; Vreugdenhil, M.; Nendel, C.; Dorigo, W. How accurately can we retrieve irrigation timing and water amounts from (satellite) soil moisture? *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *113*, 102979. [\[CrossRef\]](#)
61. Alam, M.S.; Lamb, D.W.; Rahman, M.M. A refined method for rapidly determining the relationship between canopy NDVI and the pasture evapotranspiration coefficient. *Comput. Electron. Agric.* **2018**, *147*, 12–17. [\[CrossRef\]](#)
62. Awada, H.; Sirca, C.; Marras, S.; Castellini, M.; Spano, D.; Pirastru, M. Modelling soil moisture and daily actual evapotranspiration: Integrating remote sensing surface energy balance and 1D Richards equation. *Int. J. Appl. Earth Obs. Geoinf.* **2024**, *128*, 103744. [\[CrossRef\]](#)
63. Rodrigues, H.; Ceddia, M.B.; Tassinari, W.; Vasques, G.M.; Brandão, Z.N.; Morais, J.P.S.; Oliveira, R.P.; Neves, M.L.; Tavares, S.R.L. Remote and Proximal Sensors Data Fusion: Digital Twins in Irrigation Management Zoning. *Sensors* **2024**, *24*, 5742. [\[CrossRef\]](#)
64. Martos, V.; Ahmad, A.; Cartujo, P.; Ordoñez, J. Ensuring agricultural sustainability through remote sensing in the era of agriculture 5.0. *Appl. Sci.* **2021**, *11*, 5911. [\[CrossRef\]](#)
65. Zheng, C.; Jia, L.; Menenti, M.; Hu, G.; Lu, J.; Chen, Q.; Jiang, M.; Mancini, M.; Corbari, C. Integrating hydrologic modeling and satellite remote sensing to assess the performance of sprinkler irrigation. *Geo-Spat. Inf. Sci.* **2024**, *27*, 934–952. [\[CrossRef\]](#)
66. Qian, X.; Qi, H.; Shang, S.; Wan, H.; Wang, R. Estimating distributed autumn irrigation water use in a large irrigation district by combining machine learning with water balance models. *Comput. Electron. Agric.* **2024**, *224*, 109110. [\[CrossRef\]](#)
67. Daneshgar, S.; Polesel, F.; Borzooei, S.; Sørensen, H.R.; Peeters, R.; Weijers, S.; Nopens, I.; Torfs, E. A full-scale operational digital twin for a water resource recovery facility—A case study of Eindhoven Water Resource Recovery Facility. *Water Environ. Res.* **2024**, *96*, e11016. [\[CrossRef\]](#)
68. Sharifi, A.; Tarlani Beris, A.; Sharifzadeh Javidi, A.; Nouri, M.; Gholizadeh Lonbar, A.; Ahmadi, M. Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities. *Adv. Eng. Inform.* **2024**, *61*, 102485. [\[CrossRef\]](#)
69. Paruelo, J.M.; Texeira, M.; Tomasel, F. Hybrid modeling for grassland productivity prediction: A parametric and machine learning technique for grazing management with applicability to digital twin decision systems. *Agric. Syst.* **2024**, *214*, 103847. [\[CrossRef\]](#)
70. Park, S.; Kim, J.; Kim, Y.; Kang, J. Participatory Framework for Urban Pluvial Flood Modeling in the Digital Twin Era. *Sustain. Cities Soc.* **2024**, *108*, 105496. [\[CrossRef\]](#)
71. Camps, A.; López-Martínez, C.; Gong, A.; Gracia, G.; Perez-Portero, A.; Alonso-Gonzalez, A.; Vall-Llossera, M.; Park, H.; Perez, V.; Caselles, O.; et al. AI4WATER: A Digital Twin for Irrigated Agriculture. In Proceedings of the IGARSS 2024—2024 IEEE International Geoscience and Remote Sensing Symposium, Athens, Greece, 7–12 July 2024; pp. 3545–3548. [\[CrossRef\]](#)
72. Page, M.J.; Moher, D.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ* **2021**, *372*, n160. [\[CrossRef\]](#)
73. Wangere, J.; Sinde, R.; Ally, M.; Mbwambo, O. A Digital Twin Approach and Challenges for Real-Time Automated Surface-Drip Irrigation Monitoring: A Case of Arusha Tanzania. In *Smart and Secure Embedded and Mobile Systems*; Jorge, M.G., Sam, A.E., Eds.; Springer Nature: Cham, Switzerland, 2024; pp. 47–59.
74. 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. [\[CrossRef\]](#)
75. Resh, H.M. *Hydroponic Food Production*; CRC Press: New York, NY, USA, 2022. [\[CrossRef\]](#)
76. Jans-Singh, M.; Leeming, K.; Choudhary, R.; Girolami, M. Digital twin of an urban-integrated hydroponic farm. *Data-Centric Eng.* **2020**, *1*, e20. [\[CrossRef\]](#)
77. Ropokis, A.; Ntatsi, G.; Kittas, C.; Katsoulas, N.; Savvas, D. Effects of temperature and grafting on yield, nutrient uptake, and water use efficiency of a hydroponic sweet pepper crop. *Agronomy* **2019**, *9*, 110. [\[CrossRef\]](#)
78. Rakocy, J.E. Aquaponics—Integrating Fish and Plant Culture. In *Aquaculture Production Systems*; Wiley: Hoboken, NJ, USA, 2012; pp. 344–386. [\[CrossRef\]](#)

79. Ahmed, A.; Zulfiqar, S.; Ghandar, A.; Chen, Y.; Hanai, M.; Theodoropoulos, G. Digital Twin Technology for Aquaponics: Towards Optimizing Food Production with Dynamic Data Driven Application Systems. In *Methods and Applications for Modeling and Simulation of Complex Systems*; Gary, T., Lehmann, A., Tym, C.W., Eds.; Springer: Singapore, 2019; pp. 3–14.
80. 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; pp. 522–527. [\[CrossRef\]](#)
81. Skobelev, P.; Tabachinskiy, A.; Simonova, E.; Goryanin, O. Development of crop-simulation multiagent system for smart digital twin of plant. In Proceedings of the 2022 8th International Conference on Information Technology and Nanotechnology, ITNT 2022, Samara, Russian Federation, 23–27 May 2022; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2022. [\[CrossRef\]](#)
82. Mitsanis, C.; Hurst, W.; Tekinerdogan, B. A 3D functional plant modelling framework for agricultural digital twins. *Comput. Electron. Agric.* **2024**, *218*, 108733. [\[CrossRef\]](#)
83. Verdouw, C.; Tekinerdogan, B.; Beulens, A.; Wolfert, S. Digital twins in smart farming. *Agric. Syst.* **2021**, *189*, 103046. [\[CrossRef\]](#)
84. Grieves, M.; Vickers, J. Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In *Transdisciplinary Perspectives on Complex Systems*; Springer International Publishing: Cham, Switzerland, 2017; pp. 85–113. [\[CrossRef\]](#)
85. Boyes, H.; Watson, T. Digital twins: An analysis framework and open issues. *Comput. Ind.* **2022**, *143*, 103763. [\[CrossRef\]](#)
86. Aivaliotis, P.; Georgoulis, K.; Chrysosouris, G. The use of Digital Twin for predictive maintenance in manufacturing. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 1067–1080. [\[CrossRef\]](#)
87. van Dinter, R.; Tekinerdogan, B.; Catal, C. Predictive maintenance using digital twins: A systematic literature review. *Inf. Softw. Technol.* **2022**, *151*, 107008. [\[CrossRef\]](#)
88. Momber, A.W.; Möller, T.; Langenkämper, D.; Nattkemper, T.W.; Brün, D. A Digital Twin concept for the prescriptive maintenance of protective coating systems on wind turbine structures. *Wind. Eng.* **2022**, *46*, 949–971. [\[CrossRef\]](#)
89. Lepenioti, K.; Bousdekis, A.; Apostolou, D.; Mentzas, G. Prescriptive analytics: Literature review and research challenges. *Int. J. Inf. Manag.* **2020**, *50*, 57–70. [\[CrossRef\]](#)
90. Porter, M.E.; Heppelmann, J.E. How Smart, Connected Products Are Transforming Companies. *Harv. Bus. Rev.* **2015**, *93*, 96–114.
91. Verdouw, C.N.; Wolfert, J.; Beulens, A.J.M.; Rialland, A. Virtualization of food supply chains with the internet of things. *J. Food Eng.* **2016**, *176*, 128–136. [\[CrossRef\]](#)
92. Ariesen-Verschuur, N.; Verdouw, C.; Tekinerdogan, B. Digital Twins in greenhouse horticulture: A review. *Comput. Electron. Agric.* **2022**, *199*, 107183. [\[CrossRef\]](#)
93. Alves, R.G.; Maia, R.F.; Lima, F. Development of a Digital Twin for smart farming: Irrigation management system for water saving. *J. Clean. Prod.* **2023**, *388*, 135920. [\[CrossRef\]](#)
94. Bellvert, J.; Pelechá, A.; Pamies-Sans, M.; Virgili, J.; Torres, M.; Casadesús, J. Assimilation of Sentinel-2 Biophysical Variables into a Digital Twin for the Automated Irrigation Scheduling of a Vineyard. *Water* **2023**, *15*, 2506. [\[CrossRef\]](#)
95. Rahman, H.; Shah, U.M.; Riaz, S.M.; Kifayat, K.; Moqurrab, S.A.; Yoo, J. Digital twin framework for smart greenhouse management using next-gen mobile networks and machine learning. *Future Gener. Comput. Syst.* **2024**, *156*, 285–300. [\[CrossRef\]](#)
96. Manocha, A.; Sood, S.K.; Bhatia, M. IoT-digital twin-inspired smart irrigation approach for optimal water utilization. *Sustain. Comput. Inform. Syst.* **2024**, *41*, 100947. [\[CrossRef\]](#)
97. Zohdi, T.I. A machine-learning enabled digital-twin framework for next generation precision agriculture and forestry. *Comput. Methods Appl. Mech. Eng.* **2024**, *431*, 117250. [\[CrossRef\]](#)
98. Chitu, C.; Imbrea, I.; Batrina, S.; Imbrea, F. Developing a digitaltwin model for corn, wheat and rapeseed yields computation. *Sci. Pap. Ser. Manag. Econ. Eng. Agric. Rural. Dev.* **2024**, *24*, 287–294.
99. Batarseh, F.A.; Kulkarni, A.; Sreng, C.; Lin, J.; Maksud, S. ACWA: An AI-driven cyber-physical testbed for intelligent water systems. *Water Pract. Technol.* **2023**, *18*, 3399–3418. [\[CrossRef\]](#)
100. 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. [\[CrossRef\]](#)
101. Mahmoud, M.M.M.; Darwish, R.; Bassiuny, A.M. Development of an economic smart aquaponic system based on IoT. *J. Eng. Res.* **2023**, *12*, 886–894. [\[CrossRef\]](#)
102. Sung, Y.M.; Kim, T. Smart farm realization based on digital twin. *ICIC Express Lett. Part B Appl.* **2022**, *13*, 421–427. [\[CrossRef\]](#)
103. Reyes Yanes, A.; Abbasi, R.; Martinez, P.; Ahmad, R. Digital Twinning of Hydroponic Grow Beds in Intelligent Aquaponic Systems. *Sensors* **2022**, *22*, 7393. [\[CrossRef\]](#)
104. de Campos Souza, P.V. Fuzzy neural networks and neuro-fuzzy networks: A review the main techniques and applications used in the literature. *Appl. Soft Comput.* **2020**, *92*, 106275. [\[CrossRef\]](#)
105. European Commission. Technology Readiness Levels (TRL). Horizon 2020–Work Programme 2014–2015 General Annexes, Extract from Part 19-Commission Decision C 2014. Available online: https://ec.europa.eu/research/participants/data/ref/h2020/other/wp/2018-2020/annexes/h2020-wp1820-annex-g-trl_en.pdf (accessed on 29 July 2024).

106. Héder, M. From NASA to EU: The evolution of the TRL scale in Public Sector Innovation. Volume 22. Available online: https://www.researchgate.net/publication/350942366_From_NASA_to_EU_the_evolution_of_the_TRL_scale_in_Public_Sector_Innovation (accessed on 29 July 2024).
107. Thorp, K.R.; Ale, S.; Bange, M.P.; Barnes, E.M.; Hoogenboom, G.; Lascano, R.J.; McCarthy, A.C.; Nair, S.; Paz, J.O.; Rajan, N.; et al. AGRONOMY & SOILS Development and Application of Process-based Simulation Models for Cotton Production: A Review of Past, Present, and Future Directions. *J. Cotton Sci.* **2014**, *18*, 10–47.
108. Barkakoti, C.; Joshi, S. Advancement of Digital Twin in Irrigation and Smart Farming. In Proceedings of the 2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), Erode, India, 23–25 March 2023; pp. 1245–1250. [[CrossRef](#)]
109. Xue, J.; Zhou, S.; Wang, W.; Huo, L.; Zhang, L.; Fang, X.; Yang, Z. Water availability effects on plant growth, seed yield, seed quality in *Cassia obtusifolia* L., a medicinal plant. *Agric. Water Manag.* **2018**, *195*, 104–113. [[CrossRef](#)]
110. Hong, S.S.; Lee, J.; Chung, S.; Kim, B. Fast Real-Time Data Process Analysis Based on NoSQL for IoT Pavement Quality Management Platform. *Appl. Sci.* **2023**, *13*, 658. [[CrossRef](#)]
111. Uzougbo, O.I.; Olanrewaju, O.A.; Kayode, A.K. Node-RED and IoT Analytics: A Real-Time Data Processing and Visualization Platform. (TSJPAS) A Subsid. Tech-Sphere Multidiscip. Int. J. (TSMIJ) **2024**, *1*, 3672–4648. [[CrossRef](#)]
112. Kobi, J. Developing Dashboard Analytics and Visualization Tools for Effective Performance Management and Continuous Process Improvement. *Int. J. Innov. Sci. Res. Technol. (IJISRT)* **2024**, *9*, 1697–1709. [[CrossRef](#)]
113. Raschka, S.; Patterson, J.; Nolet, C. Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. *Information* **2020**, *11*, 193. [[CrossRef](#)]
114. Sarker, I.H. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. *SN Comput. Sci.* **2021**, *2*, 420. [[CrossRef](#)]
115. Postolache, S.; Sebastião, P.; Viegas, V.; Postolache, O. Instrumentation and Measurement Systems: Digital Twin for Horticulture Farm: Concept and Requirements. *IEEE Instrum. Meas. Mag.* **2025**, *28*, 14–22. [[CrossRef](#)]
116. Arulmozhi, E.; Deb, N.C.; Tamrakar, N.; Kang, D.Y.; Kang, M.Y.; Kook, J.; Basak, J.K.; Kim, H.T. From Reality to Virtuality: Revolutionizing Livestock Farming Through Digital Twins. *Agriculture* **2024**, *14*, 2231. [[CrossRef](#)]
117. Jin, T.; Han, X. Robotic arms in precision agriculture: A comprehensive review of the technologies, applications, challenges, and future prospects. *Comput. Electron. Agric.* **2024**, *221*, 108938. [[CrossRef](#)]
118. Sindakis, S.; Showkat, G. The digital revolution in India: Bridging the gap in rural technology adoption. *J. Innov. Entrep.* **2024**, *13*, 29. [[CrossRef](#)]
119. Manivasagam, V.S. From Bytes to Farm: Transferability of Industrial Digital Twins in Agricultural Systems. *J. Biosyst. Eng.* **2025**, *50*, 130–144. [[CrossRef](#)]
120. Yin, Y.; Ma, B.; Meng, Z.; Chen, L.; Liu, M.; Zhang, Y.; Zhang, B.; Wen, C. Construction method and case study of digital twin system for combine harvester. *Comput. Electron. Agric.* **2024**, *226*, 109395. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.