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Review Article

Opportunities and challenges in the application of Digital Twins for orchard management

Xiaojuan Liu [a], Leilei He [a], Shiao Niu [a], Rui Li [a,*], Yaqoob Majeed [e], Xiaoxu Sun [f], Jinyong Chen [f], Xiaojuan Li [g], Kerry Brian Walsh [h,*], Longsheng Fu [a,b,c,d,**]

[a] College of Mechanical and Electronic Engineering, Northwest A&F University, Yangling, Shaanxi 712100, China
[b] Key Laboratory of Agricultural Internet of Things, Ministry of Agriculture and Rural Affairs, Yangling, Shaanxi 712100, China
[c] Shaanxi Key Laboratory of Agricultural Information Perception and Intelligent Service, Yangling, Shaanxi 712100, China
[d] Northwest A&F University Shenzhen Research Institute, Shenzhen, Guangdong 518000, China
[e] Department of Electrical Engineering and Computer Science, University of Wyoming, Laramie, Wyoming 82071, United States
[f] Zhengzhou Fruit Research Institute, Chinese Academy of Agricultural Sciences, Zhengzhou, Henan 450009, China
[g] Yangling Vocational & Technical College, Yangling, Shaanxi 712100, China
[h] Institute of Future Farming Systems, Central Queensland University, Rockhampton, QLD 4701, Australia

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ABSTRACT

Digital Twins (DTs) represent a new tool for enabling data-driven orchard management, with the goal of optimizing resource allocation and decision-making. However, unlike general agriculture or annual horticultural systems, fruit tree production is constrained by fixed seasonal cycles, making it difficult to conduct experiments or interventions outside these periods. In addition, the perennial nature of fruit trees, along with complex canopy structures and long production cycles, further increases the complexity and variability of orchard management. An orchard DT consists of a virtual counterpart of the physical orchard entity, with real-time integration of sensor data and a model allowing predictions of system behavior. DTs have the potential to cover all stages of tree-fruit production, from cultivation to post-harvest. This review article of the literature up to 2025 systematically summarizes and indicates that the application of DTs in orchard management remains in an exploratory stage, reflecting the state of development and adoption of enabling technologies, such as the Internet of Things, artificial intelligence, cloud computing, edge computing, extended reality, communications, and blockchain. DTs have been developed for orchard establishment, operations, harvest forecast and optimization, robotic harvesting, natural disaster response, and orchard inventory, with the dominant focus being on harvest operations. Additionally, DTs have been applied to optimize specific orchard processes, such as modelling spray droplet movement within canopies in support of the design of spraying equipment. Very few applications have involved a control system. Commonalities observed in the development of existing orchard DT models suggest the potential for a standardized or universal DT model to support expanded automation operations. Beyond routine orchard management, the potential application of DTs in areas such as natural disaster response is also highlighted, offering opportunities for cost sharing and broader cross-sector benefits.

1. Introduction

A Digital Twin (DT) represents a virtual counterpart of a physical entity, with input of real time data for monitoring and informing control of a process. Alternatively, simulated data can be used in prediction of performance of the system in an imagined scenario. As such the DT involves a representation of the physical entity and an empirical or mechanistic model of a process to enable real-time/continuous monitoring, decision-making, performance optimization and predictive maintenance, increasing production efficiency, safety and sustainability (Liu et al., 2023). For emphasis, a key aspect of a DT is that it is not a static representation of a system but that it allows for monitoring and forecast of future behavior, on time-scales that depend on the application. Mature applications can be found in the manufacturing, aerospace,

* Corresponding authors at: Institute of Future Farming Systems, Central Queensland University, Rockhampton, QLD 4701, Australia (K.B. Walsh).
** Corresponding author.
E-mail addresses: ruili1216@nwafu.edu.cn (R. Li), k.walsh@cqu.edu.au (K.B. Walsh), fulsh@nwafu.edu.cn (L. Fu).

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power, healthcare and other sectors (Singh et al., 2022; Pylianidis et al., 2021).

The integration of DTs into agricultural practices is still at an early stage, providing opportunities for innovative research. A good example of progress in this space is provided by the European Internet of Food and Farm 2020 (IoF2020) project, which spanned arable farming, dairy farming, livestock, greenhouse horticulture and organic vegetable production (Verdouw et al., 2021). The 'state of play' for agricultural DTs has been described in a number of reviews (Verdouw and Kruize, 2017; Pylianidis et al., 2021; Knibbe et al., 2022; Nasirahmadi and Hensel, 2022; Cesco et al., 2023; Wang et al., 2024; Ganapathysubramanian et al., 2025). However, reviews on the DTs in horticultural production have been limited to use in greenhouse horticulture (Ariesen-verschuur et al., 2022), general horticulture (Apeinans et al., 2023) and post-harvest management of fruit and vegetables (Rodolfo et al., 2023). To our knowledge, no review has focused to the use of DTs in tree-fruit production.

The implementation of DTs in tree-fruit production systems involves domain-specific issues distinct from those in general agricultural or annual horticultural systems. Tree-fruit systems are characterized by perennial growth patterns and seasonally evolving three-dimensional canopy architectures, which contrast to that associated with annual crops. The development of tools to capture a digital representation of tree canopies, such as LiDAR technologies (Agerpoint, 2022), has become a key enabler in the creation and advancement of orchard DTs.

This review documents current research trends on the application of DTs in orchard management by searching literature during the period from 1998 to 14 May 2025, detailing foreseeable opportunities and potential challenges. The use of DTs in post-harvest applications has been covered in the recent review by Rodolfo et al. (2023), and is therefore not be discussed in the current review. The review is organized as follows: Section 2 describes the review methodology. Section 3 introduces the enablers and limiters to DT adoption. Section 4 presents the applications of DTs in orchards as reported in literature. Section 5 considers the future for orchard DTs, in context of drivers for adoption and the recommendation of a universal DT platform to support multiple providers of orchard automation equipment. Section 6 summarizes the conclusions of this work.

2. Literature review methodology

2.1. Research questions

The following research questions were set: (i) What is the definition of a DT and what are the enabling technologies of DTs in the context of tree-fruit production? (ii) What is the current status and trends in existing literature with respect to implementation of DTs in tree-fruit production? (iii) What are the foreseeable opportunities, potential challenges, and countermeasures for the use of DTs to enhance orchard management?

2.2. Literature search strategy

The databases of Engineering Village, Web of Science, and Google Scholar for the period from 1998 to 14 May 2025 were searched using the keyword combination "(digital twin*)" AND "(orchard OR vineyard OR viticulture)", and "(digital twin*) OR (digital twins) OR (digital clone) OR (virtual twin) OR (digital double) OR (cyber replica) OR (virtual replica)" AND "(orchard OR vineyard OR viticulture OR fruit* OR apple* OR kiwifruit* OR orange* OR mango* OR citrus* OR grapefruit* OR lemon* OR peach* OR litchi* OR grape* OR strawberry* OR blueberry* OR cherry* OR pineapple* OR pomegranate* OR jujube*)". A snowball method was also adopted, based on references in the articles located in the database search (Klerkx et al., 2019). Papers were initially screened based on title and abstract, and then based on text content, with respect to relevance to the keywords and research questions.

3. Background: Enablers and limiters to DT adoption

3.1. Concept origin and definition

The concept of a DT as a virtual counterpart to a physical entity originated in the early 2000s through collaborative work by Michael Grieves and John Vickers of the National Aeronautical Space Administration (NASA) (Grieves, 2014; Attaran and Celik, 2023). At that time, digital representations of physical products were immature, with most information being manually collected and paper-based. Grieves (2014) conceptualized a DT as comprised of three main parts: (i) physical products in real space; (ii) virtual products in virtual space; and (iii) the connections of data and information that ties the virtual and real products together.

In a more recent definition of a DT, Clark et al. (2019) involved the same components but highlighted use in managing or understanding the system. The components were: (i) a physical object; (ii) real-time data integration, ensuring continuous updates with information from the physical counterpart; (iii) simulation and modeling capabilities to test various scenarios; and (iv) a feedback loop that uses DT insights to improve the physical object or system. Moreover, Tao et al. (2018) provided a useful summary of twinning as involving six steps: (i) a virtual product; (ii) analysis and visualization of data; (iii) simulation of behavior; (iv) control of behavior; (v) feedback to the virtual product; and (vi) re-measurement of real world data (Fig. 1).

The cycle between the physical and virtual states has been described as mirroring or twinning (Jones et al., 2020). Later, Grieves and Vickers (2017) positioned DTs in terms of product life cycle, with use in monitoring, management, and improvement of a product throughout its life cycle. An early practical implementation of a DT involved an high-fidelity simulation of a space vehicle (Grieves and Vickers, 2017). Subsequent applications emerged in manufacturing industries, exemplified by Siemens, General Electric, US Air Force, Oracle, ANSYS, SA, and Altair (Pylianidis et al., 2021), as well as the applications in other sectors followed (Jones et al., 2020).

There is effectively no universal definition of a DT (Tao and Qi, 2019), with numerous definitions used across various disciplines. The definitions used in the reviewed literature on orchard DTs (Semeraro et al., 2021; Verdouw et al., 2021; Rasheed et al., 2020) are illustrated in the Fig. 2 and Table 1. It can be clearly seen that, in addition to these keywords of physical, virtual, digital, and twin, the DT definition also highlights the involvement of data and modeling.

An orchard management DT should therefore involve a virtual representation of an orchard or a component of it, the collection of real-time data for different application scenarios (either from the real world or a simulation), the simulation and modeling of a process occurring in the orchard, and the control of an object in real world to effect a change in the orchard. Such 'real time' control will require actions at different time scales depending on the application, e.g., seconds in the control of spray nozzles, and hours in the control of irrigation, days in the forecast of harvest maturity.

3.2. Enabling technologies for DTs

The technologies underpinning a DT were summarized by Tao et al. (2018) (Fig. 1). These technologies include Internet of Things (IoT), communication networks, Artificial Intelligence (AI), edge computing, cloud computing, Virtual Reality, and blockchain technologies. The IoT is based on use of Internet Protocol addresses, enabling a network of sensor and control devices that are connected through the internet, exchanging data. Of course, this interchange requires a communication infrastructure to support this data exchange. Data analysis can either occur on edge computing devices or on a cloud computer. Increasingly more sophisticated tools (i.e., AI) are being used in data analysis for

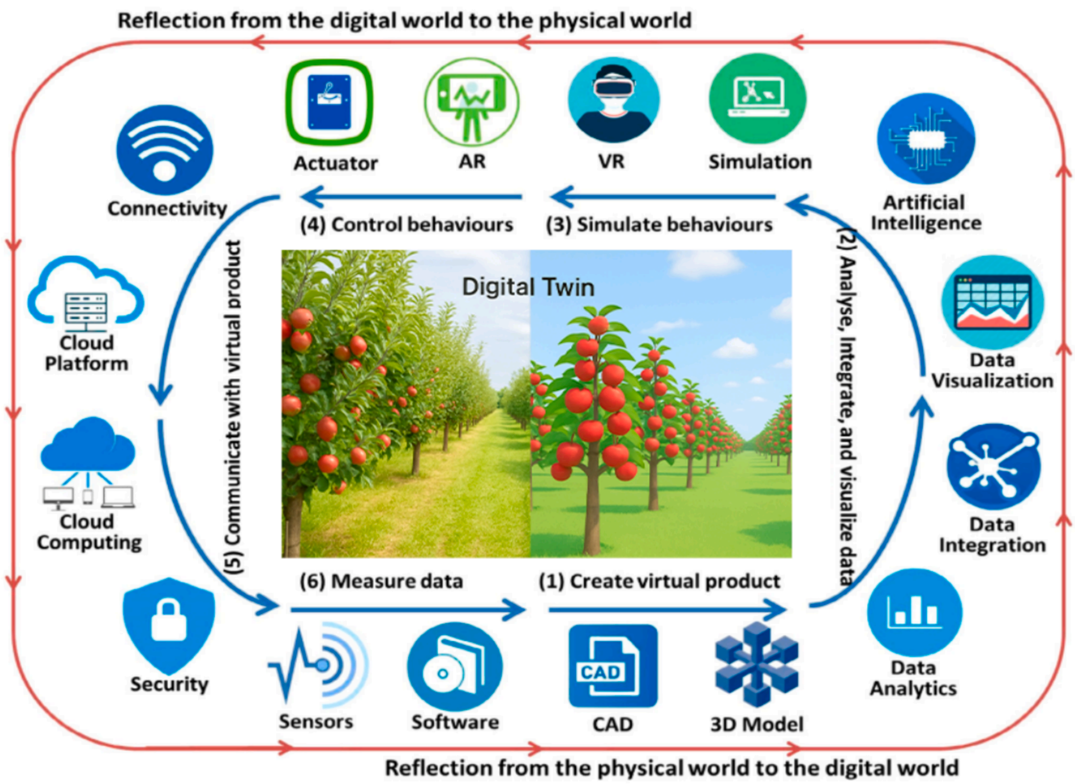


Fig. 1. Six steps involved in a DT and enabling technologies (Tao et al., 2018).

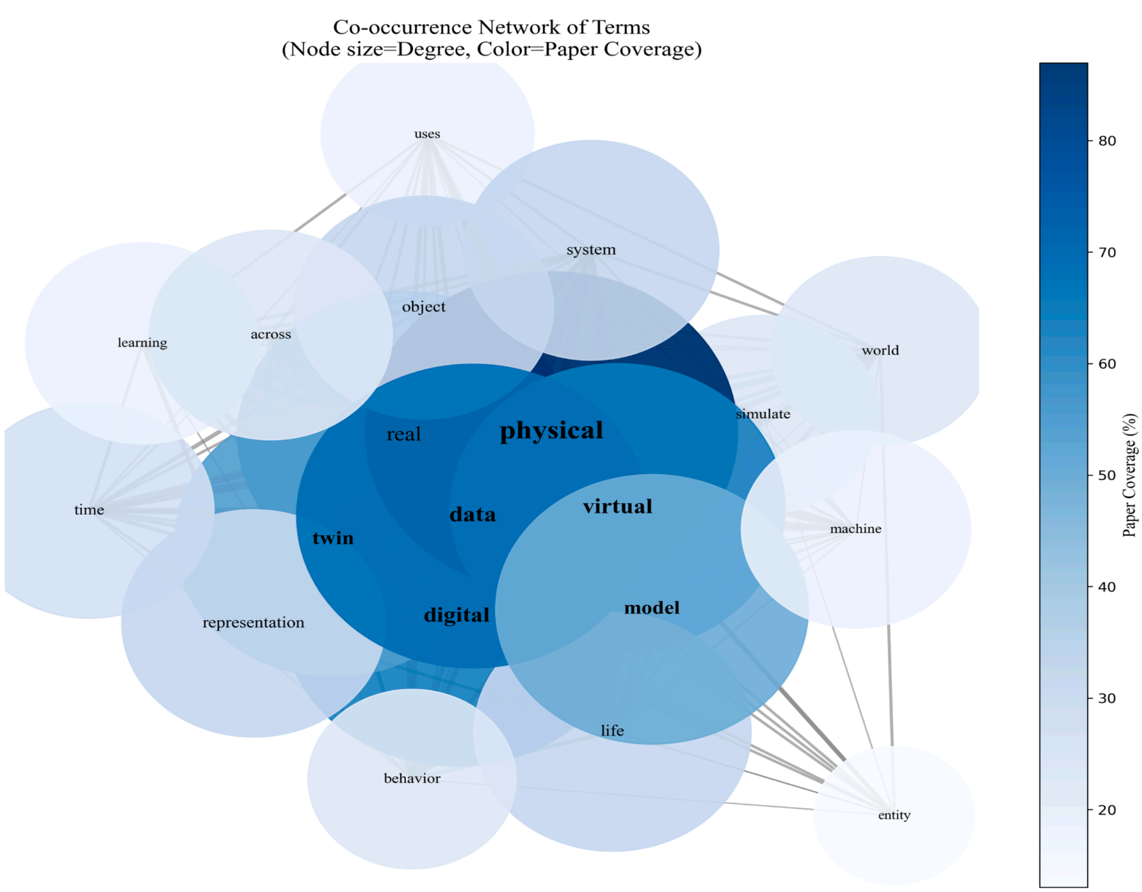


Fig. 2. Top 20 keywords co-occurrence network of the definitions of DTs used in the reviewed literature. The color scale on the right side of the figure corresponds to the percentage of keywords appearing in the definitions of DTs.

Table 1
Top 20 keywords frequency and co-occurrence statistics of the definitions of DTs used in the reviewed literature of 24 papers. Degree refers to the number of co-occurrences of keywords, Percentage represents the frequency of the keywords, and Paper_Percentage indicates the paper coverage.

Keyword	Count	Percentage (%)	Degree	Paper_Percentage (%)
physical	31	5.77	211	86.96
data	18	3.35	189	65.22
digital	24	4.47	184	60.87
virtual	18	3.35	171	60.87
real	13	2.42	169	56.52
twin	16	2.98	153	52.17
model	16	2.98	149	47.83
system	10	1.86	99	30.43
representation	8	1.49	106	30.43
object	8	1.49	102	30.43
life	8	1.49	117	30.43
time	6	1.12	95	26.09
behavior	6	1.12	66	21.74
world	6	1.12	73	21.74
simulate	5	0.93	81	21.74
across	5	0.93	90	21.74
machine	5	0.93	80	17.39
uses	4	0.74	69	17.39
learning	5	0.93	83	17.39
entity	6	1.12	39	13.04

predictive analytics and adaptive optimization, given the size of the data sets involved. A human user requires a Graphical User Interface (GUI) to interact with such systems, with developments in Virtual Reality (VR) (also known as Extended Reality (ER), Augmented Reality (AR) and Mixed Reality (MR)) providing technology to blend the display of virtual world information on a human users view of the real worlds. Blockchain is a digital distributed ledger technology enabling secure and transparent record keeping.

Edge computing: In an edge-computing architecture, processing, analysis and control occur in real-time at the network's edge (Tao et al., 2020). For instance, data from a temperature sensor network was analyzed using a LSTM (Long Short-Term Memory) model deployed on an edge computing platform (Jetson AGX Xavier, NVidia, USA) for frost prediction in crops. The best LSTM model achieved a deviation less than 1 °C (Guillén et al., 2021). The use of edge computing devices allows distributed computing that maintains operational continuity under limited connectivity. However, this paradigm incurs capital costs and maintenance needs at the 'user-end'.

Cloud computing: The use of a cloud computing resource shifts these requirements to a specialist provider, and provides for scalability, i.e., fluctuation in computing load. The use of cloud platforms can therefore simplify the task of implementing a DT (Attaran and Celik, 2023), given communication infrastructure of appropriate bandwidth and reliability to allow synchronization between physical and digital orchards. Azure FarmBeats (FarmBeats, 2017) attempts to provide a generic commercial platform for implementation of cloud based agricultural DTs, provided at no additional cost over the use of the cloud resources (i.e., elastic computing resource and data storage). For example, Vasisht et al. (2017) presented FarmBeats, an IoT platform for agriculture that enables data collection from various sensors.

Connectivity: A DT requires physical-digital connectivity through distributed sensor networks, enabling the collection of data related to the environment (soil and air) and the plant. The communication pathway must allow bi-directional traffic if control operations are to occur, as well as data collection. The development of standardized protocols, such as 5G, LORA, LORA-WAN, Wi-Fi, and Zigbee, provides for device interoperability (Peladarinos et al., 2023) (Fig. 3). The choice of communication technology is dependent on the application need in the context of bi-directionality, bandwidth, and frequency.

A tree-fruit DT may involve data collection frequency that varies from sub-second to annual depending on the application. For instance, over seconds and minutes in the context of light interception or spray drop movement through a canopy, hours to days for irrigation scheduling, years for tree canopy development, and decades for expansion of plantings. Protocols such as 5G and LoRa achieve sub-second latency in data exchange from field based sensors and control systems (Rayhana

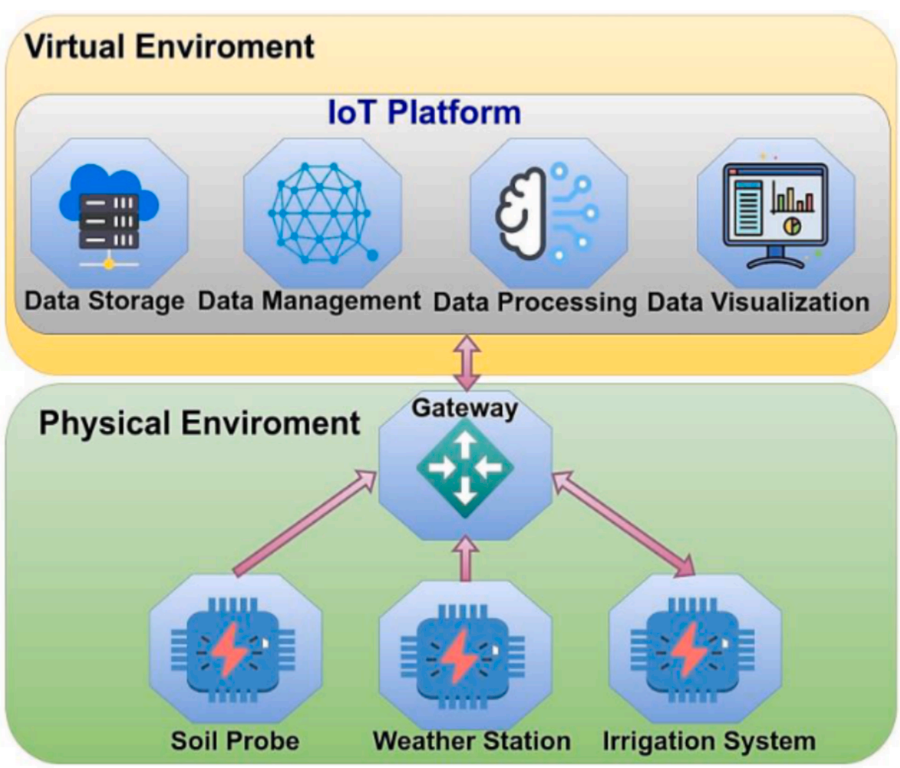


Fig. 3. Example of connections between the virtual and real world over an IoT platform in Digital Twinning (Peladarinos et al., 2023).

et al., 2021), with Wi-Fi implementations demonstrating a peak throughput of 9.6 Gbps for high-density sensor deployments (Peladarinos et al., 2023).

The choice of communication technology is also driven by the bandwidth required, i.e., the size of the data packets. A LoRa network is adequate for the transmission of small data packets, while a higher bandwidth solution is required for the transmission of images. For example, LoRa was used in the acquisition of environmental data, such as temperature, at 15-minute intervals, from a kiwifruit orchard (Dhonju et al., 2024), while 5G was used to transmit images captured by a mobile phone to detect leaf diseases (Lin et al., 2024). Imaging the whole orchard, e.g., using RGB imaging at 15 fps to enable fruit detection, tracking, and counting, or LiDAR imaging for canopy rendering of the orchard, involves data sets of a size that are currently impractical to move to a cloud computing resource in farm implementation (as opposed to research trials), driving use of edge computing for these applications.

Blockchain: Blockchain introduces cryptographic trust mechanisms into DTs. It provides reliable and confidential solutions for product traceability, peer-to-peer exchanges, contracts, and digital representations of physical assets within the tree fruit supply chain (Lombardi et al., 2018). For example, immutable ledgers were used to record grapevine graft cycles and the progression of Brix increase with fruit development, and to host contracts based on quality parameters (Li et al., 2019).

Virtual Reality: Virtual Reality technologies facilitate synergistic interaction between physical objects and their digital counterparts, enabling simultaneous visualization of actual and virtual objects. For instance, AI-guided grapevine pruning suggestions were visualized by a human field operator using a mobile AR application running on a smartphone (Häring et al., 2024). A similar system that presented information regarding tomato fruit harvest candidates obtained from image processing on a cloud computer, with User Datagram Protocol (UDP) communication with a Mixed Reality Head Mounted Display (MRHMD) providing information to workers in real-time for immediate decision-making (Ryota et al., 2022).

Artificial Intelligence: The last decade has seen an explosion in the use of increasingly sophisticated prediction algorithms, moving from simple linear regression to techniques such as random forest, neural networks, and more recently Large Language Models (for text and language-based tasks). For example, a random forest model providing a forecast of bloom density for use in precision flower thinning (Knibbe et al., 2022).

Three-dimensional (3D) reconstruction: Another enabler for the development of orchard DTs has been the development of technologies that capture a digital representation of tree canopy. Notable examples include Light Detection and Ranging (LiDAR) and 3D reconstruction from multi-view point RGB imagery using techniques such as Structure from Motion (SfM) or guassian splatting. For instance, LiDAR-enabled mobile devices were used in a commercially available application that allows the creation of tree DTs (Agerpoint, 2022), and a spinning 3D LiDAR was utilized in an automated dynamic canopy monitoring system generating orchard-scale DTs (Moghadam et al., 2020).

3.3. Limiters to DT adoption

Notable limiting factors in context of DTs for tree-fruit production is that of general poor connectivity in rural areas, the relatively low economic scale of many tree-fruit farms compared to that of industries in which DTs have been adopted, with a resulting shortage of IT-skilled labor on farm and difficulty in funding technology implementation (Godawal et al., 2024). The state of development of the enabling technologies mentioned earlier is another issue, with the state of their development being potential limiters to the adoption of a DT. For example, while the development of solid-state LiDARs promises increased robustness and lower cost compared to traditional spinning LiDARs, its performance is only now reaching parity with the established spinning technology (Christian and Sebastian, 2022; Wang et al., 2022). This slower-than-anticipated maturation directly impacts the feasibility of deploying cost-effective, high-fidelity 3D sensing systems for critical orchard DT applications like precise canopy mapping, fruit load estimation, and growth monitoring in challenging outdoor environments.

4. Applications of DTs in orchards

4.1. Overview

The content of the reviewed papers was summarized in terms of technology used and application served (Table 2). The reviewed papers were categorized based on: (i) commodity and production systems, (ii) technology used, and (iii) management need (Fig. 4).

4.2. Commodities and production systems

DT applications in tree-fruit production have occurred primarily in the commodities of stone fruit (apple, cherry, and pear) orchards, vine (grapevine and kiwifruit) orchards, and citrus and tropical fruit (citrus, mango, and litchi) orchards (Table 2). In general, the orchard DT applications involved high-density production systems, due to their high capital and maintenance costs per unit area. Application examples also exist in orchard systems that are more extensive but highly mechanized, such as citrus, while the application to mango and macadamia production is nascent.

Many tree-fruit production systems, with apple cultivation being a prominent example, are transitioning toward high-density fruiting-wall architecture (Majeed et al., 2020) (Fig. 5). Trees are typically trained to a trellis (Gao et al., 2020), such as T and V trellises for kiwifruit and vineyards, respectively (Fu et al., 2019; Majeed et al., 2021) (Fig. 6). These systems are more capital intensive to establish than a traditional layout, but produce higher returns per unit of land in a shorter time. The higher investment per unit area and more intensive management favors the adoption of additional management aids, such as the DTs.

As these systems are designed to maximize light interception, there is markedly less occlusion of fruit and foliage than in traditional tree architectures. This structural characteristic facilitates the effective use of external sensing technologies, including RGB-D cameras and LiDAR sensors, for representative canopy data acquisition. Furthermore, the similar cultivation structures allow the transfer of best practices and insights gained from one orchard to others.

4.3. Applied technologies

4.3.1. Sensors

Rapid advancements are occurring in sensor technology, with decreasing cost, increasing robustness and ease of use being enablers of the adoption into DTs for orchard management. The sensors are deployed either in a stationary position, or on a mobile platform, either space (satellite), air (UAV) or ground based. The primary sensors used in the reviewed papers were LiDAR, high-resolution RGB and hyperspectral systems, with use in 3D reconstruction of tree canopies, and in detection of canopy attributes. For example, several studies deployed UAVs equipped with photogrammetric cameras and LiDAR (Edemetti et al., 2022; Meyer et al., 2023; Kodors et al., 2023; Zarembo et al., 2023).

LiDAR hardware using spinning technology, such as the Riegl AZ-400i (Riegl, Horn, Austria) (Han et al., 2024), the SICK LMS511-20100 (SICK AG, Waldkirch, Germany) (Lowe et al., 2021), and the Leica RTC3 60 terrestrial laser scanner (Leica Geosystems, Heerbrugg, Switzerland) (Castro, 2025) was used in the reviewed literature. Examples of RGB-depth cameras used in the reviewed literature include the ZED 2 stereo camera (Stereolabs, San Francisco, USA) (Castro, 2025). Multispectral cameras included the MAPIR Survey3W (MAPIR Inc, San

Table 2
Summary of reviewed literature in terms of commodity and application case, and technologies employed. 'Spinning' refers to the mounting of sensors to a mobile platform that is moved through the orchard.

Citation	DT case	Commodity	Sensors	Computing and communication	Technologies and simulation software	Application
Moghadam et al. (2020)	√	Mango, Macadamia, Avocado, Grapevine	LiDAR (Spinning), Cameras	–	AgScan3D+	Automated dynamic canopy monitoring system for support precision agriculture decision-making and intelligent management of orchard production systems
Lowe et al. (2021)	√	Grapevine	SICK LMS511-20100 LiDAR scanner (Spinning)	–	SLAM	Dynamic monitoring and estimation of canopy density of perennial horticultural crops (such as vineyards) for precision agricultural decision-making and mechanical automation support
Han et al. (2022)	√	Apple	Riegl AZ-400i LiDAR scanner (Spinning)	GeForce RTX 2070, Quadro RTX 4000, and GeForce RTX 3060 Ti	LIGHT and SPRAY modules	Orchard design and spraying optimization
Edemetti et al. (2022)	√	Grape	LiDAR, 4K video camera, Hyperspectral camera, Proximity sensors	DIWINE project platform, 5G	Unity 3D modeling software, AI, Machine Learning (ML)	Comprehensive and precise orchard management
Zarembo et al. (2023)	–	Apple, Pear, Cherry	RGB camera	–	Deep Learning (DL)	Orchard monitoring for yield forecasting
Mawson et al. (2023)	√	Apple	Not described	–	–	Build a dynamically coupled DT of apple's production and supply chain systems, achieve 'end-to-end' optimization from single fruit trees to global supply chains through multidisciplinary model integration and real-time and dynamically updated data streams
Meyer et al. (2023)	√	Cherry	Photogrammetric camera	For5G project platform, 5G	3D Reconstruction	Orchard DT for monitoring and manipulation of tree growth
Kodors et al. (2023)	–	Apple, Pear, Cherry	RGB Camera, GPS	–	AI, BPMN, UML, 4 EM, ARTSS, and OPM	Yield forecasting and estimation
Pickering et al. (2023)	√	Kiwifruit	RGB cameras, GPS, Inertial Measurement Unit (IMU), and lighting	Microsoft Azure platform, Edge Computing, Communication (WIFI, 4G, ROS)	AI, ROS	Modular Agritech Systems for Horticulture (MAS-H) to systematically address efficiency, sustainability, and labor shortage in the kiwifruit industry
Du et al. (2023)	–	Apple	Not described	Semantic communication	AI, DL	Monitor orchard status and optimize management decisions- picking path planning and communication resource allocation
Bellvert et al. (2023)	√	Grapevine	Soil moisture sensors, Sentinel-2	IrriDesk (Cloud-hosted platform), ZENTRA cloud platform, IoT and satellite communication	Soil Water Balance (SWB) model	Automated irrigation scheduling
Tian et al. (2023)	√	Apple	RGB camera	–	Unity 3D modeling software, Reinforcement Learning (RL), ML-agent plugin	Robot picking arm path planning
Wang et al. (2023)	√	Litchi	Not described	–	Unity 3D modeling software, VR, RL, SolidWorks, 3ds Max, UGUI, XCharts, Socket	Implement a DT that allows for simulation of the operational behavior of mobile robots in a virtual orchard environment
Zanchin et al. (2023)	√	Grapevine	Nikon DSLR camera	–	Photogrammetry technique, 3D Reconstruction, Metashape	Analyze the morphology of grape bunches, extract alternative traits (volume and surface correlation, global morphological parameters, compactness related parameters) for bunch varieties classification and compactness evaluation
Han et al. (2024)	√	Mango, Grape	Riegl AZ-400i LiDAR scanner (Spinning), RiScan Pro	High-performance computing platform	Random-walk model	Mitigate orchard spray drift
Onwude et al. (2024)	√	Orange	–	–	EPIC crop growth model, Empirical regression models	Quantify impact of growing conditions on the harvest quality of oranges
Ruiz et al. (2024)	√	Grapevine	GPS, IMU	–	Siemens STAR-CCM + software, Lagrangian Particle Model (LPM)	Build a DT of unmanned aerial spraying systems to simulate spray deposition in a virtual vineyard environment, optimize nozzle configuration and flight control strategies to reduce pesticide drift

(continued on next page)

Table 2 (*continued*)

Citation	DT case	Commodity	Sensors	Computing and communication	Technologies and simulation software	Application
Zanchin et al. (2024)	√	Grapevine	RGB camera	–	Photogrammetry technique, 3D reconstruction, Metashape	Extract grape bunch morphology features for the whole DT reconstruction of grape bunches, quantify the association between grape bunch morphology and gray mold risk to evaluate the risk of grey mold infection
Catala-roman et al. (2024)	–	Orange	–	–	Photogrammetry technique, OpenDroneMap	Monitoring, land planning and management, optimization of fertilizers or pesticides, yield analysis and crop forecasting
Kim and Heo (2024)	√	Mandarin	–	–	Interface applet, ML	Develop an interactive R Shiny platform to achieve single-plant management, provide customized decision support, display real-time data and historical trends at the orchard and individual tree level to promote the transition from precision agriculture to individualized agriculture
Yao et al. (2024)	√	Litchi	Not described	–	Unity 3D modeling software, SketchUp, 3ds Max, SolidWorks	Model of virtual orchard and simulation of picking behavior of a harvesting robot
Castro (2025)	√	Apple	Stereo camera (ZED 2), Multispectral cameras (MAPIR Survey3W), Terrestrial laser scan (TLS) Leica RTC360 LiDAR (Spinning), Emlid Reach RS2 GNSS receiver, IMU	NVIDIA Jetson Nano	DL, Agisoft Metashape, CloudCompare	Build an orchard DT through multi-sensor fusion and AI to achieve real-time health monitoring with immediate responsiveness and precision agricultural decision-making

Note: Business Process Modeling Notation (BPMN), Unified Modeling Language (UML), Enterprise Modelling (EM) methodology, and Object Process Methodology (OPM); –, not available.

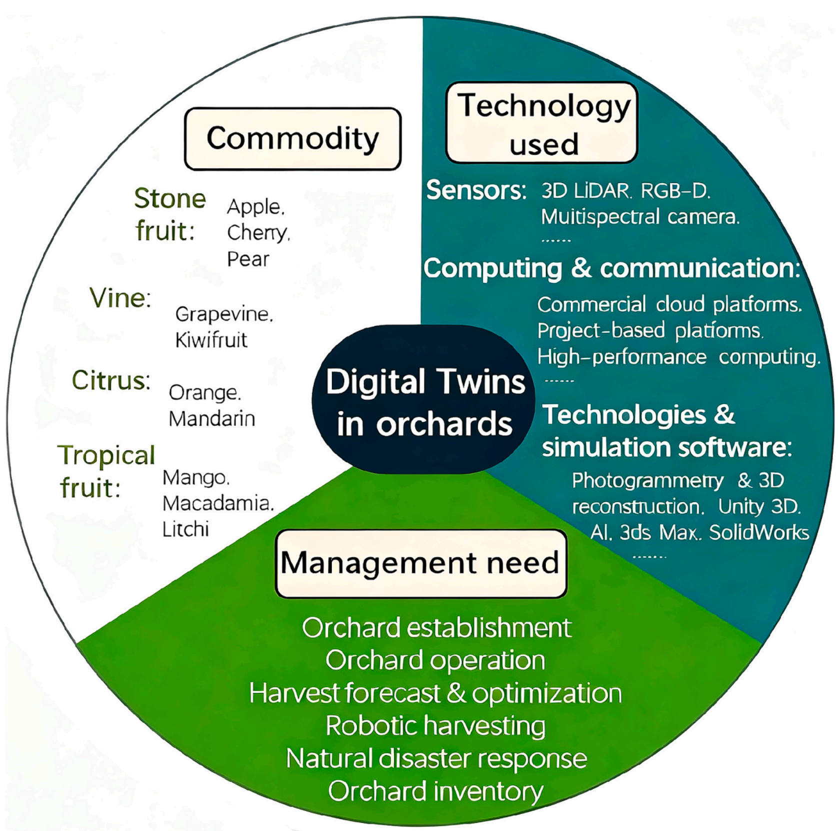


Fig. 4. Overview of the applications of DTs in orchards in terms of commodity, technology used, and management need, as documented in referred articles published between 1998 and 14 May 2025.

(a) (b)

Fig. 5. Modern apple orchard cultivation pattern. (a) Fruiting-wall architecture of apple orchard (Gao, 2022); (b) The tree architecture tied by wires in a modern orchard (Gao et al., 2020).

(a) (b)

Fig. 6. Kiwifruit orchard and vineyard cultivation pattern. (a) T-trellis structure of kiwifruit orchard (Fu et al., 2019); (b) V-trellis structure of vineyard (Majeed et al., 2021).

Diego, USA) (Castro, 2025).

4.3.2. Computing and communication

An orchard DT will include both relatively 'small' and 'big' data sets. For example, the LiDAR point cloud of a 2 ha mango orchard generated by Stein et al. (2016) involved collection of 1.3 million points per second collected over a 3-hour period by a Velodyne HDL64E LiDAR, generating a 42.12 GB data set, while a 15 fps 5 MP RGB imaging system operated on a ground vehicle moving at 10 km/h past 3 km of tree row in a 2 ha orchard generates 9.3 GB of data per session. In comparison, the total data volume across 13 weeks of monitoring of 10 soil moisture sensors at hourly intervals was only 87 KB (32-bit floating-point soil moisture data at 4 bytes/sample) (Stein et al., 2016).

The storage and processing of big-data sets may be beyond the capacity of edge computing hardware, while use of cloud computing resources is dependent on robust and cost-effective communication infrastructure. However, edge computing capacity is rapidly increasing. For example, the NVIDIA Jetson Nano (NVIDIA, USA) debuted in 2019 as an edge computing device featuring 472 GFLOPS (NVIDIA, 2019). It has been implemented to reduce cloud dependence in low-bandwidth farmland environments, but exhibited performance bottlenecks when dealing with high-resolution data or multi-tasking (Castro, 2025). Three years later, the Jetson AGX Orin was released (NVIDIA, 2022), delivering 200–275 200 (TOPS) within a 100 × 87 mm form factor, supporting real-time and actionable image processing for in-orchard machine vision applications, e.g., as used in Anderson et al. (2021). The Jetson Thor, released in October 2025, offers twice the processing capacity of its predecessor.

The computing and communication resources required to support a DT are contingent upon the application requirements. For instance, Han et al. (2022) created a DT of a tree-fruit canopy to study the movement of spray droplets from sprayer through the tree canopy, aiming to optimize sprayer design and set-up. This simulation required use of university-based high-performance computing infrastructure. In contrast, local server infrastructure has been used for on farm applications, including: (i) orchard irrigation management (IrriDesk, Bellvert et al., 2023); (ii) real-time/sensor-driven monitoring of cherry tree growth status (For5G, Meyer et al., 2023); and (iii) UAV-based multispectral imaging for grapevine yield forecast (DIWINE, Edemetti et al., 2022).

The selection of a local or cloud resource is a foundational decision in the design of a DT. A local server with appropriate capacity can be used, providing data security, but this requires initial capital expenditure and local expertise for maintenance of the resource, with a DT for orchard management and control require greater hardware resources than a typical personal computer. The use of a local resource is certainly appropriate when computing infrastructure is in place, such as at a university or research facility, and where the task involves design rather than direct orchard management. However, the typical farm is unlikely to have capacity for maintenance of such hardware. Therefore, practical application of orchard DTs is likely to involve the use of cloud resources, as allowed by communication infrastructure.

Commercial cloud platforms such as Amazon Web Services (AWS) and Microsoft Azure provide advantages in scalability, reliability and reduced operational complexity, while challenges in the use of these systems include vendor dependency and data security risks. In a representative implementation, Pickering et al. (2023) adopted the Azure cloud platform (Microsoft, Redmond, USA) for implementation of an orchard DT for kiwifruit human-assisted harvesting and flower bud thinning. Microsoft has taken a step beyond provision of computing resource to provide 'Azure Farm Beats' (Vasisht et al., 2017) for aggregation of farm data and development and deployment of AI models. This represents the first step towards provision of a generic tool for deployment of orchard DTs.

The implementation of cloud computing in real-time and operationally relevant orchard management requires high speed data transmission and low latency, achievable by 5G and Wi-Fi networks. However, communication infrastructure in the rural areas where orchards are typically situated is generally significantly less developed compared to that in urban areas. The emergence of broadband satellite internet services like StarLink™ (Redmond, Washington, DC, USA), delivering download speeds of up to 220 Mbps with upload speeds typically between 5 and 20 Mbps across stationary and mobile stations, has revolutionized commercial orchard management and marketing (Dhonju et al., 2024). On-going advancements in infrastructure and communication technologies are expected. For example, semantic communication enables improved information transmission (Du et al., 2023).

Communication can be enhanced by optimizing network coverage, implementing redundancy and backup mechanisms. Standardized interfaces, communication protocols and unified platforms can ensure better system coordination and reliability, strengthening scalability and interoperability (Ariesen-verschuur et al., 2022). These needs are not unique to orchard applications, with a similar need recognized for smart city DTs (Mohammadi & Taylor, 2021).

4.3.3. Technologies and simulation software

Photogrammetry and 3D reconstruction technologies are required to portray the orchard environment. An array of simulation and modeling technologies have been employed in the development of orchard DTs, including Siemens STAR-CCM+ (Siemens, Texas, USA), SketchUp (Trimble, Sunnyvale, USA), 3ds Max (Autodesk, San Rafael, USA), and SolidWorks (Dassault Systèmes, Waltham, USA). A recent comparative analysis of 3D point cloud tools identified OpenDroneMap as a preferred tool for point cloud processing for orchard DTs (Catala-roman et al., 2024). Commonly used visual notation tools for modeling, like 4EM for project view, ARTSS for logical view, OPM for process view, IoT-adapted UML component diagram for physical view, and spatial map for deployment view, offer a roadmap for design and development of smart solutions in fruit-growing to predict the yield and potential of income generation in the early stages of the season (Kodors et al., 2023).

Unity 3D (Unity Technologies, San Francisco, USA) was used in several of the reviewed publications. It has been used to create intricate 3D models of orchard canopy environments (Tian et al., 2023; Wang et al., 2023; Yao et al., 2024). This software developed out of the game industry (Peladarinos et al., 2023) and allows for bidirectional data transfer. Its physics engine and programming functionalities have been used to support robot path planning and operational training (Tian et al., 2023).

A range of other software have been used in the creation of orchard DTs. AI, ML, DL, RL, and ML-Agent plug-ins have been widely used for data analysis and decision-making. For instance, Edemetti et al. (2022) described the development of a DT using sensor-equipped UAVs, a 5G network and Multi Access Edge computing (MEC) enabled ML/AI data processing to remotely control the UAVs and to transfer captured high-resolution images to the cloud. Tian et al. (2023) employed an ML-Agent plug-in for RL for training the robotic arm movements involved in fruit picking.

Several specialized modules have been developed that can be integrated into an orchard DT. A LPM model was specifically used to evaluate the effectiveness of spraying operations (Ruiz et al., 2024). An EPIC crop growth model was adopted for forecast of the growth and quality of orange fruit based on input of environmental parameters (Onwude et al., 2024). The SWB models have also been developed. For example, one model allows for discontinuous canopies and drip irrigation systems in row-structured vineyards (Bellvert et al., 2023). Other examples of modules that could be used in orchard DTs include the modules LIGHT and SPRAY, as described by Han et al. (2022). LIGHT is used for generation of 3D DTs of orchard canopy designs, with a use case of the simulation of the light environment within a canopy. SPRAY is used for generation of 3D DTs of chemical sprayer, with use for evaluation of spray equipment and canopy architecture to maximize spray penetration into the canopy.

These models have generally been developed for an 'in-house' use with limited accessibility. The public or commercial release of such resources and a set of software tools used in creating an orchard DT (Table 2) would allow the development of a resource 'library' that would speed the development of orchard DTs. Peladarinos et al. (2023) also summarized a series of data bases, development tools, and 3D simulation software on DTs in smart farming, thereby providing a valuable reference for the development and application of orchard DTs.

In addition to the enabling technologies described in Section 3.2, research on DTs for orchard management has not yet involved VR and blockchain technologies. VR can offer an immersive interface for interacting with orchard DTs. By visualizing 3D orchard structures, growth dynamics, and environmental influences, VR supports intuitive interpretation of complex datasets. Simulated scenarios (harvesting, irrigation, or equipment operation) enable low-cost, risk-free training and strategy testing. Multi-user functions further allow geographically distributed experts to collaborate in a shared virtual orchard, enhancing remote diagnostics and decision support. Integrating VR with DTs thus advances precision management through improved visualization, training efficiency, and collaborative problem-solving.

Blockchain enhances orchard DTs by securing heterogeneous data from sensors, UAVs, and machinery within tamper-resistant ledgers. This ensures data integrity and traceability, strengthening model credibility. Smart contracts enable automated applications, including fruit traceability, agrochemical compliance, and carbon credit trading, linking orchard data with certification and financial mechanisms. For instance, pesticide records or carbon sequestration estimates generated by DTs can be stored on-chain for transparent verification. The integration of blockchain thus not only reinforces data trustworthiness but also creates economic and sustainability value across the orchard supply chain.

4.3.4. Growth and associated models

Extensive literature exists on digital orchard representations, but the definition of a DT necessitates bidirectional feedback mechanisms in which the DT is used in orchard management. To move beyond a simple remote operation, in which a human operator is making decisions based on DT representation rather than by in-field manual observation, requires the development of models or algorithms that can be implemented in a decision support system. Such models can be mechanistic or empirical. The development of models or algorithms in decision support systems is thus pivotal to advancing mechanized operations in DT orchards.

Such models are required for every orchard task the DT intends to address. For example, Wang et al. (2023) established an autonomous learning and decision-making model based on a deep RL algorithm to optimize orchard establishment management. Substantial research efforts have yielded predictive models aiming to forecast of tree and/or fruit growth (Ribeiro et al., 2018; Zhao et al., 2019; Bai et al., 2020). The Malusim apple tree model includes a fruitlet growth rate model, a carbohydrate model, and an irrigation model that could be used as 'rules' with a DT. Representative implementations encompass the EPIC growth model for orange fruit (Onwude et al., 2024), and the LIGHT and SPRAY models on light scattering and spray movement through the canopy (Han et al., 2022).

The use of AI-based data analysis will increase, given the size and complexity of the data sets involved in a DT of an orchard. For instance, ML algorithms have been adopted in plant health and yield forecasts (Ariesen-verschuur et al., 2022), while DL has been employed in image recognition tasks, like pest and disease identification (Syed-Ab-Rahman et al., 2022).

4.4. Management need

The published applications of the use of DTs in tree-fruit production focus to orchard establishment, operations, harvest forecast and optimization, robotic harvesting, natural disaster management, and orchard inventory (Table 2). These applications can also be categorized based on the end user. For production staff, DTs serve as a valuable tool for orchard management, while for other stakeholders, the technology offers solutions to optimize specific processes, such as designing tree layout in establishing an orchard or establishing a spray system for a given canopy architecture.

4.4.1. Orchard establishment

Orchard establishment in the context of tree and row spacing and layout of blocks and services is critical to future production, influencing tree health, resource utilization, and fruit quality. For example, Han et al. (2022) proposed the DigiHort solution allows users to create 3D DTs of orchard designs, allowing pre-evaluation of the impact of factors such as row orientation, tree spacing, canopy size, and terrain on light distribution in the orchard. Han et al. (2024) developed a DT-based solution to simulate orchard characteristics and spray processes that closely mirror reality. It enables high simulation fidelity and aims to serve as a decision-support tool for practical operations. A subsequent investigation demonstrated that the spray drift in the same orchard environment can be reduced by 36 % through simple modifications of sprayer settings. Such outputs cannot only be used to optimize the adjustment of traditional equipment, but can also be loaded to robotic or automatic sprayers to make them more precise and responsive, yet simpler and cheaper. Therefore, using the variable-rate sprayers allows for the implementation of digital twinning recommendations at a tree level, rather than at an orchard block level.

It is reported that a digital apple orchard is being built by John Mawson and his research team at Plant & Food Research (2022), representing innovative advancements in orchard DTs. This initiative constitutes part of the work New Zealand scientists from Plant & Food Research, involving the full production continuum from cultivation to postharvest distribution. Current literature reveals limited research efforts in developing DTs for specialized horticultural crops, but no-one is tackling this challenge for perennial fruit crops with the same wide view as Plant & Food Research's program. The implementation of this project by New Zealand scientists is expected to provide vital guidance for orchard establishment through data-driven optimization. Subsequently, Mawson et al. (2023) incorporated likely market pricing into a DT addressing apple production, allowing production recommendations to be informed by market signals.

4.4.2. Orchard operation

The operation of an orchard requires continual decision making around factors such as irrigation, pruning and pest control. Currently, orchard management is typically conducted at the block level, where each block consists of trees with a consistent management history. Given access to tree-level data and an appropriate data handling system, DTs can support the precision agriculture goal of individualized plant management (Kim and Heo, 2024). Meyer et al. (2023) developed a DT involving real-time/sensor-enabled monitoring of the status of individual trees based on regular UAV surveys. For example, the effect of the environment on the plant can be assessed more accurately. Furthermore, the collected representative data can support the farmer in recognizing critical conditions of individual trees, such as drought stress, nutrient deficiency or pest infestation. Moghadam et al. (2020) presented an automated dynamic canopy monitoring system (AgScan3D +), which consists of a spinning 3D LiDAR plus cameras that can be retrofitted to a farm vehicle, to generate a DT of every tree on a large orchard scale.

Examples follow for a range of management tasks:

Irrigation and fertilization: Irrigation and fertilization is currently typically provided at an orchard block level, or at best on a row basis, given limitations on the control of irrigation water. Fertilization can be achieved through irrigation (fertigation), spraying foliage or the spreading of granular fertilizer. Precision application at tree level necessitates dedicated valvular infrastructure per tree. Bellvert et al. (2023) developed a DT-driven automated irrigation decision-making system involving integration of Sentinel-2 satellite, soil moisture sensor and meteorological station data. Their cloud-based implementation of the SWB model enabled dynamic simulation of crop evapotranspiration and generation of daily deficit irrigation prescriptions on a row basis. Complementary studies by Alves et al. (2019, 2023) have further demonstrated DT applications in precision irrigation. Yogeswaranathan et al. (2024) and Peladarinos et al. (2023) also demonstrated how DTs implementations facilitate simulation of integrated various farming tasks like irrigation, fertilization, nutrient management, and pest control, providing real-time with immediate responsiveness data and guiding farmers through 'what-if' scenarios.

Fruit growth: Kim and Heo (2024) presented a DT for mandarin crop monitoring and decision support, while Onwude et al. (2024) employed a digital replica using inputs of weather conditions and cultivation practices and a mechanistic model of fruit growth to forecast of the orange growth from fruit set to harvest to predict the quality of the fruit at harvest (Fig. 7). The DT of orange fruit predicts temperature profiles, heat transfer, respiration, rind thickness, sugar and acid content.

Pest and disease control: Zanchin et al. (2023, 2024) developed a DT for grey mold infection risk assessment. Multi-angle photography and Metashape 1.7.2 (Agisoft LLC, Saint Petersburg, Russia) software was used to build a high-precision three-dimensional DT model of grape bunches. Geometric parameter extraction and statistical analysis was used to improve the accuracy of gray mold risk prediction and also for classification of varieties. In another example, Castro (2025) utilized multispectral, stereo vision and LiDAR data in a monitoring and decision support DT platform for apple detection and plant health assessment. In fact, the DT control function in this research currently remains at the "semi-automatic" recommendation level, and needs to be combined with human decision-making or future hardware expansion (such as agricultural robots) to achieve closed-loop control.

Individualized tree-level management: Kim and Heo (2024) integrated data soil chemical properties, fruit sugar content and size, weather information and agricultural practice data into a DT that allowed visualization and analysis at regional, inter-orchard, and intra-orchard scales. ML algorithms were used in the application platform based on R Shiny (RStudio PBC, Boston, USA) to display real-time and historical data both at the orchard and individual tree levels (Fig. 8).

Automation: Tree-fruit production involves many repetitive tasks involving the use of machinery. DTs can be employed to facilitate automation of tasks such as orchard mowing, flower bud and fruit thinning, pollination, chemical spraying, pruning and harvest. The reviewed papers gave greatest focus to the use of DTs in the automation of fruit harvesting. For example, Pickering et al. (2023) proposed a DT as part of a human-robot collaborative systems for kiwifruit harvesting and flower bud thinning, while Yao et al. (2024) documented a virtual modeling approach for optimization of mechanical harvesting of litchi, and Tian et al. (2023) used a simulated environment in reinforcement learning for training of stone fruit harvesting robots.

A regularly updated virtualization of orchard canopy structure could be used in support of automation of multiple orchard tasks. Modern tree orchards are planted to RTK-GNSS derived co-ordinates, i.e., at spacings accurate to within 10 cm, however the canopy line of a tree row is irregular, with some branches leaning further into the inter-row. This can trigger obstacle avoidance strategies in automated equipment operating on RTK-GNSS and sensing for obstacle detection. A regularly updated canopy reconstruction based on LiDAR or RGB-depth camera data would be very useful for path planning of automated machinery

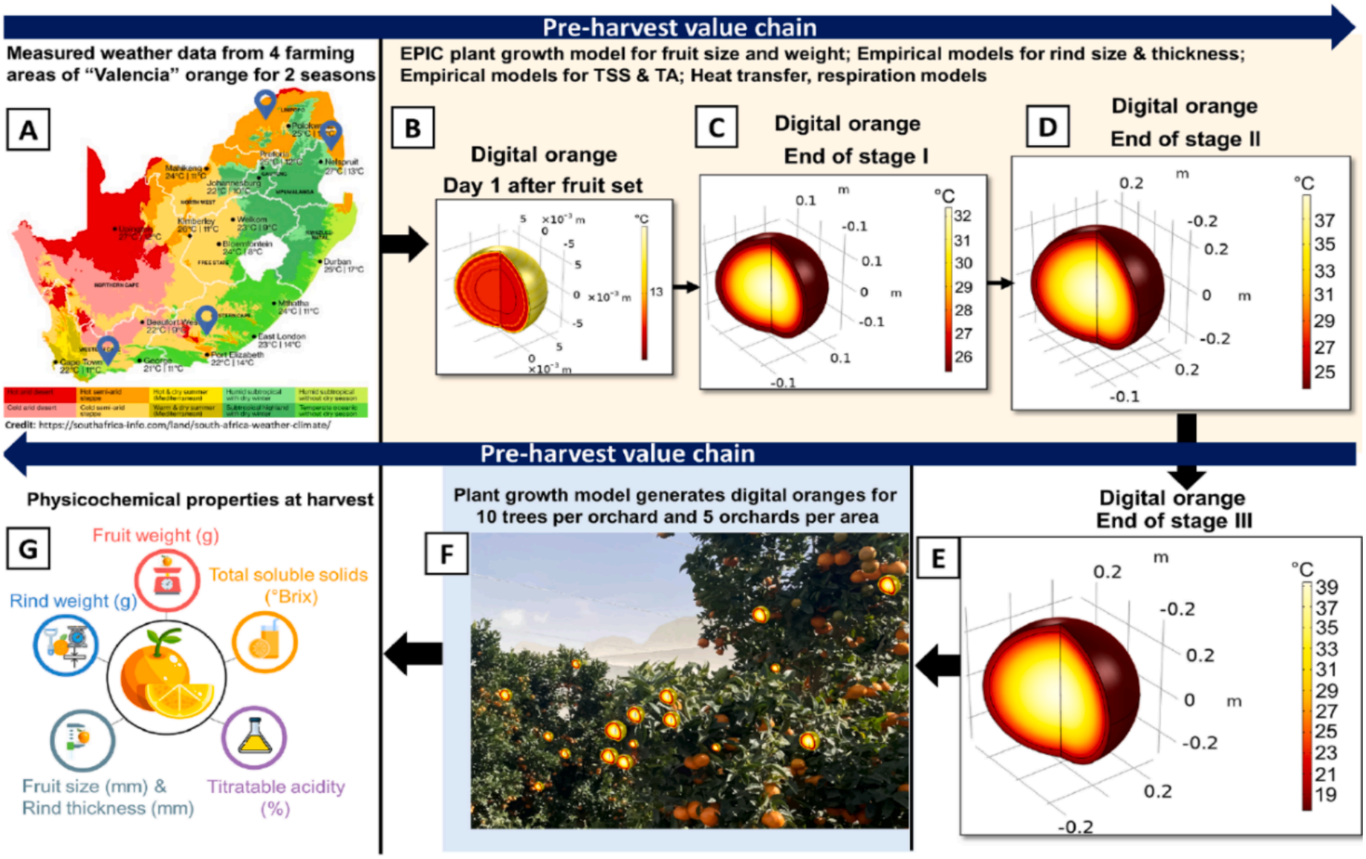


Fig. 7. A flowchart of the overall methodology implemented from weather data collection to the fruit quality at harvest (Onwude et al., 2024).

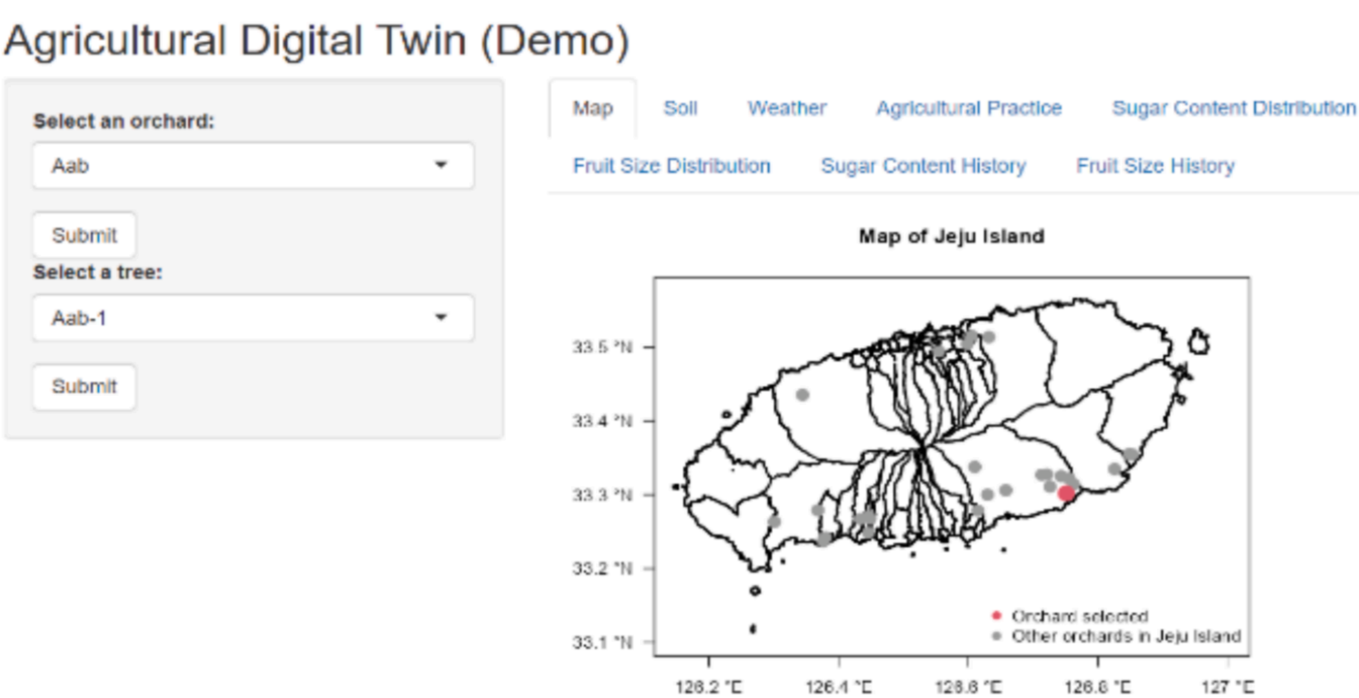


Fig. 8. Agricultural DT interface applet (Shiny DT). The provided information include geographic location of the orchard, regional soil components with RDA recommendations and comparison to other orchards in Jeju Island, weather information with comparison to the other orchards, agricultural practices with comparison to the other orchards, inter- and intra-orchard comparison of sugar content, inter- and intra-orchard comparison of fruit size, inter- and intra-orchard history of sugar content, and inter- and intra- orchard history of fruit size (Kim and Heo, 2024).

and for task allocation, such as for pruning of wayward branches.

Task optimization: Applications of DTs also exist outside of orchard management *per se*, i.e., in the optimization of equipment or processes to be used in the orchard. Wang et al. (2023) implemented a DT that allowed for simulation of the operational behavior of mobile robots in a virtual orchard environment (Fig. 9). In another use case, Han et al. (2024) used a canopy DT to conduct modelling of spray droplet movement in support of the design of spray equipment.

4.4.3. Harvest forecast and optimization

The forecast of harvest load (fruit quantity and quality) and steps to modify this (fruit thinning, irrigation, use of reflective mulch, etc.) are critical to the planning of the harvest operation in terms of labor and material resourcing, and to the marketing of the crop. Harvest management information systems have been developed that integrate temperature data, manual or machine vision estimates of flowering, handheld near-infrared spectroscopy assessments of fruit maturity, and manual or machine vision estimates of fruit number and size to generate forecasts of harvest load and the optimal timing of harvest (Kodors et al., 2023) (Fig. 10). For example, Dhonju et al. (2024) presented such an information system for mango. Adding a simulation function to create a DT, Edemetti et al. (2022) created a DIWINE DT platform in which the yield and quality of harvest could be forecast under various scenarios (Fig. 11).

4.4.4. Robotic harvesting

The use of DTs in robotic harvesting is a specific application of DTs in equipment optimization, as mentioned in the previous section. Tian et al. (2023) employed Unity 3D software to plan the path of a robotic harvesting arm path, using and used an ML-Agent plug-in for RL in training the movement to improve the accuracy of placement of the gripper to the fruit (Fig. 12). A DT would involve transfer of the movements and effects generated within the virtual environment to a physical world scenario (Tian et al., 2023). Of course, the fidelity of the DT in terms of time scale and physical resolution will determine the success of a transfer from virtual word to real world. For example, the tree virtualization in Fig. 12 does not provide detail on minor branches or trellis, nor occlusions of fruit by leaves or other fruit, and does not incorporate a physics-driven model of canopy (and remaining fruit) movement upon harvest of a fruit.

DTs could also be used in facilitating remote human collaboration during the harvesting process. Pickering et al. (2023) presented two case studies involving kiwifruit human-assisted harvesting and flower bud thinning, utilizing Modular Agritech Systems for Horticulture (MAS-H) integrated with an DT (Fig. 13). The system was developed on the Microsoft Azure platform with the aim of reducing the life cycle costs associated with research, development, and operation. In the kiwifruit human-assisted harvesting case (Fig. 13a), the DT was created for a device intended to assist workers in picking kiwifruit, consisting of a fruit catcher, fruit transport subsystem, and fruit box loader. In the flower bud thinning case, a DT of flowers on vines was used in labor allocation decision support (Fig. 13b), with the creation of worker task allocations involving directions on where to go, the most appropriate flower bud thinning strategy, and an expectation of time based on the knowledge-based rules.

4.4.5. Natural disaster response

Similar to use in smart city DTs used in disaster decision-making, DTs in orchards can be developed to enhance real-time or sensor-enabled monitoring, impact assessment, and recovery strategy optimization. DTs can be used to simulate impacts like fire, frost, and flood (Bascietto et al., 2018; Maysara, 2022), contributing to orchard resilience and operational continuity (Maysara, 2022). Of course, the reliability of sensor and communication in a disaster situation is an issue (Qiu et al., 2023). Processing large datasets for timely disaster responses also demands powerful computing power and advanced data processing technologies (Kanungo and Jain, 2023). These challenges are also present in most applications of DTs in orchards.

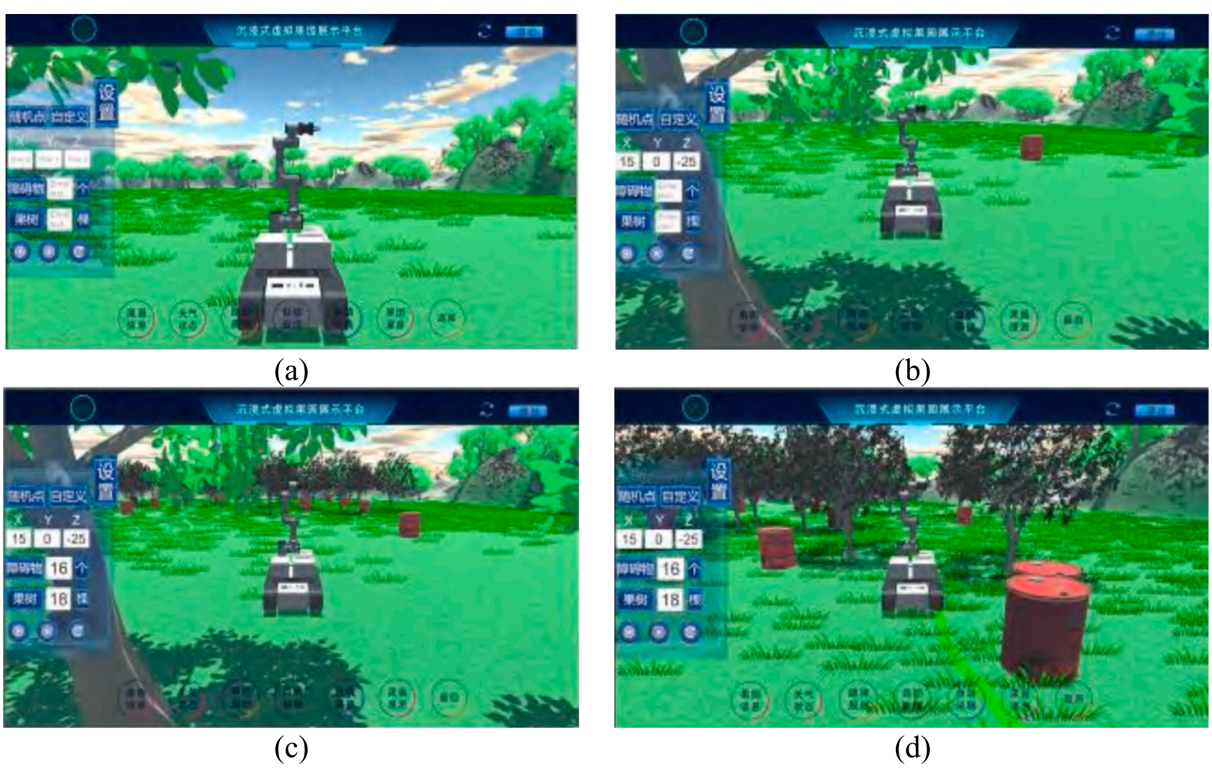
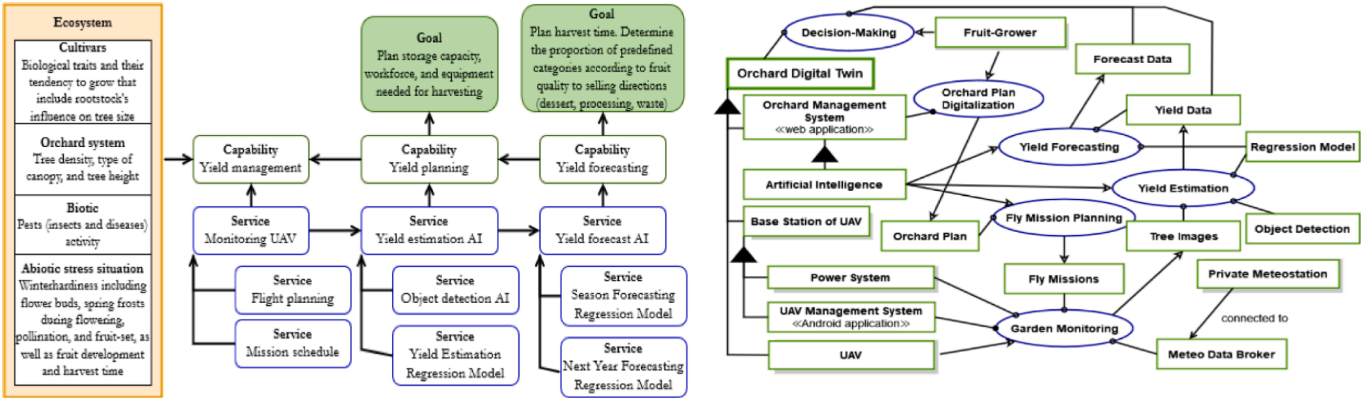
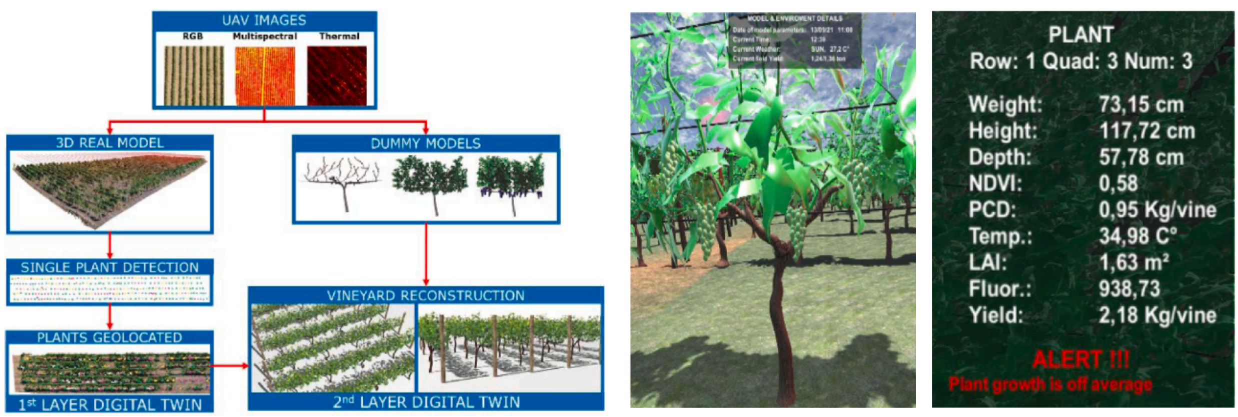


Fig. 9. Reframing event and decision simulation process in a litchi orchard. (a) The initial state of a virtual scene; (b) The position of a custom obstacle, and the red oil barrel in the scene represents the obstacle; (c) The number of obstacles and fruit trees is randomly set; (d) The autonomous obstacle avoidance path planning process of a mobile robot, where the green trajectory is the moving trajectory of the picking robot (Wang et al., 2023).



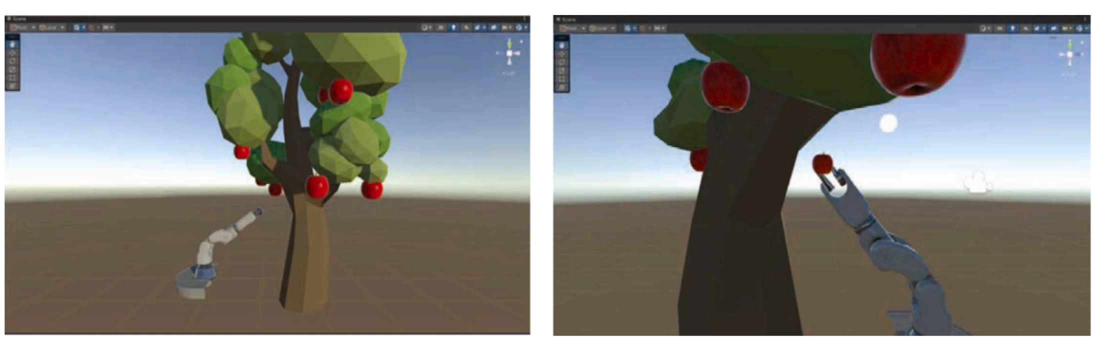
(a) (b)

Fig. 10. Roadmap for the design and development of intelligent solutions in fruit-growing of a smart orchard DT. (a) Capability model of a smart orchard DT; (b) Object process diagram of the smart orchard (Kodors et al., 2023).



(a) (b) (c)

Fig. 11. DT construction and weather changes focus on two different aspects in a vineyard. (a) DT construction of two-layer; (b) Plant status focus on grapes and weather parameters; (c) DT plant with alert point parameters and tips (Edemetti et al., 2022).



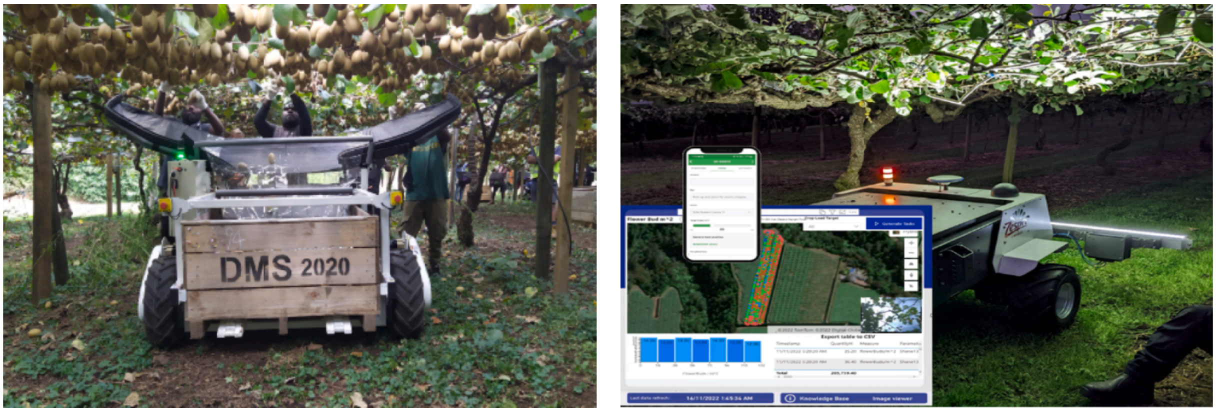
(a) (b)

Fig. 12. Process of a robotic arm picking fruit in a DT platform. (a) Example of a DT used in training of a robotic harvester movements; (b) The robotic arm successfully picks up an apple (Tian et al., 2023).

Such a disaster management capability would most likely be provided by a government, while utilizing farm-deployed sensor networks as dual-function infrastructure serving both emergency response and precision orchard DTs. The implementation framework necessitates establishing public–private data sharing protocols, and cost-sharing mechanisms through institutionalized public–private partnership. Such collaborative architecture enables synergistic utilization of governmental emergency management resources and agricultural producers' orchard-level IoT infrastructure.

4.4.6. *Orchard inventory*

An ancillary application of comprehensive orchard DT could be the occasional access of data for asset documentation purposes. Representative implementations cases contain recording fruit yield metrics for insurance settlements or orchard transactions, and monitoring fertilization regimes coupled with soil moisture dynamics for regulatory



(a) (b)

Fig. 13. Implementation of the Modular Agritech Systems for Horticulture (MAS-H). (a) Human-assisted harvesting robot using MAS-H; (b) In-orchard data capture of kiwifruit flower buds for labor decision support using MAS-H (Pickering et al., 2023).

compliance with watershed management protocols (Kim and Heo, 2024). Commercial LiDAR-based farm inventories solutions are available within agricultural technology markets, such as Agerpoint (Agerpoint Inc, Sarasota, USA), DroneDeploy (USA), and Zenmuse L1 (China) establishing operational precedents.

5. The future for orchard DTs

5.1. Drivers for orchard DT adoption

Although the benefits of DTs in agriculture are widely recognized, their practical implementation in real-world agricultural settings has not advanced as rapidly as in industrial and manufacturing fields (Liu et al., 2023; Dawn et al., 2023). Unlike manufacturing systems governed by well-defined physical principles, orchard biological processes remain insufficiently modeled. Additionally, large-scale orchards generate massive datasets under limited communication bandwidths, necessitating edge computing solutions for localized data processing. While sensor technology has advanced rapidly, it remains costly, complex, and often lacks the robustness required in harsh field environments.

The adoption of DTs in tree-fruit production systems depend strongly on achieving favorable cost-benefit ratios through operational implementation. This economic imperative disproportionately incentivizes adoption within large-scale operations utilizing intensive cultivation frameworks, specifically high-density plantings with fruiting wall canopy architecture. Importantly, the creation of a tree fruit DT must remain purpose-driven, providing clear, operation-specific benefits while also supporting long-term orchard sustainability.

One factor in the successful adoption of DT technology is the usability of the product. Current DT implementations predominantly focus on addressing specific tasks, exemplified by structural optimization of tree structure or canopy layout for optimal light interception. However, time-poor orchard managers are likely to be unwilling to learn multiple systems, coming in addition to the many systems already involved in managing an orchard. A universal DT platform with modular, user-selectable functions would therefore enhance adoption. Furthermore, as noted earlier, shared data infrastructures, supported by public–private partnerships, may also distribute costs and increase accessibility among several groups.

DTs can further accelerate adoption by acting as an enabler for other technologies. For example, Unmanned Ground Vehicle (UGV) applications in orchards are increasing, with commercial units offered by Burro (Philadelphia, Pennsylvania, USA) and XAG (Guangzhou, Guangdong, China). These units are used in weed and canopy spraying and mowing. At present, they primarily rely on RTK-GNSS for navigation (Fountas et al., 2022), with sensor and edge computing for obstacle avoidance. Thus, as multiple orchard tasks become automated, a frequently updated canopy DT would provide value in serving multiple uses, including pruning and harvesting. There is no doubt that some key enabling factors for orchard applications include multi-source sensing (LiDAR, hyperspectral imaging, and IoT-based sensors), predictive analytics, and scalable edge-cloud architectures.

As most current studies remain at the visualization or simulation level, future research on orchard DT adoption should focus on advanced applications as a promising direction, which is crucial for the development of fully interactive and autonomous orchard DT systems. First and foremost, researchers should prioritize the development of models that accurately capture biological processes at both the canopy and fruit scales. To address computational bottlenecks, hybrid edge–cloud architectures are needed, where data from sensors like LiDAR and hyperspectral imaging are processed locally before transmission to the cloud. Equally important is the establishment of robust cost–benefit evaluation frameworks that quantify the economic and environmental impacts of DT adoption across different orchard scales and production systems. In addition, secure and cooperative data-sharing mechanisms, potentially enabled by blockchain technologies, should be explored to reduce costs and foster collaboration among growers, researchers, and equipment suppliers. Finally, research should investigate methods to balance the integration of specialized DT functions, such as pruning optimization, within universal DT platforms that remain simple and user-friendly for orchard managers.

5.2. Recommendation for a universal DT

A DT cannot realistically model all aspects of the real world but should instead focus on those elements most critical to the application under consideration. For instance, a DT for light distribution in orchards must require detailed information on canopy surfaces, light extinction coefficients, and illumination sources. Nevertheless, as mentioned earlier, usability is undermined if orchard managers are forced to operate multiple independent DT systems. Therefore, a universal DT platform, equipped with model plug-ins, would recommend to provide flexibility while minimizing user burden. Achieving this vision requires robust standardization. Harmonized data structures, protocols, and communication interfaces, together with standardized metadata, sensor specifications, and measurement units, would reduce integration barriers, enhance interoperability, and improve scalability while lowering costs for both developers and users.

The standardization in protocols and data formats required for a universal DT will promote interoperability and thus scalability (Peladarinos et al., 2023). While enhanced usability for orchard managers can be achieved through intuitive dashboards, configurable alert systems, and immersive VR interactive displays, non-standardized data formats and proprietary protocols increase integration complexity, expand the 'digitization footprint', and demand considerable effort for data harmonization and system adaptation. Non-standardization is likely to result in difficulty for small, innovative developers to introduce features into the DT 'ecosystem'. Moreover, sensor calibration errors, incomplete environmental modeling, and high computational costs for real-time and actionable simulation can further constrain DT accuracy and scalability. Overcoming these limitations will be critical for realistic evaluation and sustainable deployment of orchard DT systems.

Another critical concern is uncertainty and error propagation, often overlooked in DT design. Sensor measurements inherently include noise, and these inaccuracies can propagate through canopy reconstruction, climate modeling, or task planning modules, leading to amplified errors in predictions. For example, small deviations in soil moisture or light measurements can lead to significant inaccuracies in irrigation scheduling or light distribution simulations. To mitigate these effects, DT frameworks should embed uncertainty quantification and propagation analysis using methods such as Bayesian inference (Benos et al., 2021) and Monte Carlo simulation (Lowe et al., 2021). Providing confidence intervals or uncertainty maps alongside predictions improves transparency, enhances decision support, and strengthens user trust, thereby making DT systems more robust and applicable in real-world orchard management.

One pathway for the development of orchard DTs lies in the advancing use of automated systems in orchard operations. Multiple providers of task-specific equipment, such as equipment for slashing, pruning, spraying, and harvesting, could benefit from access to a shared, dynamically updated three-dimensional canopy representation of an orchard. Such a common resource would not only enhance navigational capabilities and task coordination but also establish a foundational framework for an orchard DT. By promoting interoperability among different machines and data systems, it would enable more efficient, safe, and data-driven orchard management, laying the groundwork for scalable digital transformation in perennial fruit production.

Another developmental path for orchard DTs builds on the expansion of irrigation control systems, which arguably represent the most prevalent remotely operated orchard management tool. Irrigation control is based on the input of soil sensors, plant parameters such as trunk diameter, and weather data, with the output of recommended irrigation events coupled to a system of remotely actuated pumps and irrigation valves. Such a system could be expanded into a more complete orchard DT involving inputs of soil moisture, light levels, tree health, canopy architecture, and/or fruit size, with outputs of optimal irrigation and fertilization scheduling, pest control actions, harvest timing, and forecasts of fruit number and size at harvest (Kim and Heo, 2024).

A long-term vision for the orchard (towards 2050) includes predictive phytopathology, irrigation, and canopy management systems. These applications require the integration of multi-sensor inputs (RGB, hyperspectral imaging, LiDAR, environmental sensing, insect and spore trap counts) within a DT framework that allows pre-emptive management action, such as automated spraying, under the approval of a human manager. In such a system, updated 3D orchard canopy models would guide autonomous machinery and feed predictive models for disease outbreaks, fruit load estimation, and precision spraying. Progress within the growing ecosystem of developers and agricultural technology providers, as highlighted in the 2024 Interpoma Congress, makes this vision realistic.

Future research on universal orchard DTs should focus on creating standardized communication protocols and open-source APIs for interoperability across sensors, robots, and platforms. Integrating uncertainty quantification methods, such as Bayesian inference and Monte Carlo simulations, will enable probability maps and confidence intervals for yield forecasts. Error-correction algorithms based on multi-sensor fusion, combining LiDAR, RGB, and hyperspectral imaging, are also critical to minimize inaccuracies in canopy reconstruction and environmental modeling. Modular plug-in architectures should be developed to allow orchard managers to activate or deactivate functions, such as harvest scheduling or pest monitoring, without reconfiguring the entire DT platform. Furthermore, close integration with autonomous machinery must be pursued, enabling DT-guided navigation and dynamic task allocation in real orchard environments. Finally, research should advance long-term DT modeling frameworks that simulate multi-year orchard dynamics, including the effects of pruning, disease spread, and yield variability, thereby transforming DTs into predictive and prescriptive tools for sustainable orchard management.

6. Conclusions

This work presented a literature review on the applications of DTs in orchard systems. It mainly reviewed how DTs serve as an innovative new tool to support smart and data-driven orchard management. The comprehensive analysis revealed that the adoption of DTs in orchard management remains in an exploratory phase, reflecting the state of development and adoption of some enabling technologies underpinning a DT. The concept of DTs is not being explicitly defined within the context of orchard applications. These reviewed studies demonstrated that DTs have been developed for orchard management and focus on supporting harvest operations, with some achieving promising preliminary outcomes. DTs have the potential to cover all the stages of tree-fruit production, from cultivation to post-harvest. This review also found that a standardized or universal DT model for reference is essential and suggested to enable expanded automated operations applications of DTs in orchards. Beyond routine orchard management, the potential application of DTs in natural disaster response was highlighted. These findings constitute critical prerequisites for advancing operational DT implementation in precision orchard management.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

CRediT authorship contribution statement

Xiaojuan Liu: Conceptualization, Investigation, Methodology, Supervision, Writing – Original draft, review & editing. **Leilei He:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Shiao Niu:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Rui Li:** Writing – review & editing, Supervision, Conceptualization. **Yaqoob Majeed:** Writing – review & editing, Supervision, Conceptualization. **Xiaoxu Sun:** Writing – review & editing, Investigation, Conceptualization. **Jinyong Chen:** Writing – review & editing, Investigation, Conceptualization. **Xiaojuan Li:** Writing – review & editing, Methodology, Conceptualization. **Kerry Brian Walsh:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Longsheng Fu:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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