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# A 3D functional plant modelling framework for agricultural digital twins

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#### ABSTRACT

Digital twins are a core industry 4.0 technology enabling the virtual replication of real-world objects, mimicking behaviours and states throughout their lifespan. While digital twins have shown significant benefits in industries such as manufacturing, transportation, and healthcare, their application in agriculture is still within its infancy. Their realisation also poses significant challenges, such as the creation of dynamic agricultural objects (e.g., plants). Existing literature on digital twins in agriculture identifies their limited ability to monitor physical objects without predictive capabilities and that there is a significant lack of 3D representations of plants with functional attributes. Yet, incorporating 3D representations of plants with underlying functionality in a digital twin can greatly improve growth, yield, and disease prediction accuracy. This enhancement enables various applications, such as assessing and developing pruning strategies, providing education to growers, guiding pruning robots, and optimizing spraying techniques. To that end, Functional Structural Plant Modelling presents a potential solution by representing the 3D architecture of plants and incorporating the functionality of different plant parts. By conducting a domain analysis of 3D plant phenotyping and FSPM, this study addresses the specific needs of digital twins in agriculture regarding FSPM. The investigation bridges the existing knowledge gap by identifying crucial concepts, including 3D plant modelling with underlying functionality and 3D plant phenotyping for digital twins. Specifically, a framework for 3D FSPM integration into agricultural digital twins is proposed. The framework not only acknowledges the associated requirements and challenges identified in existing literature but also lays foundation for the advancement of digital twins in the agricultural domain.

#### 1. Introduction

Digital twins (DT) represent a fundamental technology (Huang et al., 2021), enabling the recreation of physical objects within a virtual environment, faithfully reproducing their characteristics and behaviour over time (Boschert & Rosen, 2016; Grieves & Vickers, 2017). This innovative concept has attracted considerable attention across various industries, including manufacturing, healthcare, and transportation, due to the technology's potential to enhance efficiency, reduce costs, and improve decision-making (da Silva Mendonça et al., 2022). For example, Burke et al (2019) listed the DT as one of the top 10 strategic technology trends in 2019, and in 2020, it was identified as an emerging technology for the next 5-10 years (Tao et al., 2022). However, the adoption of DT in agriculture and logistics, which are integral parts of the food chain, has been relatively low, accounting for less than 2 % and 4 % of reviewed applications, respectively (Uhlenkamp et al., 2022). In a review conducted by Ariesen-Verschuur et al. (2022), a total of only eight articles were identified that specifically address the topic of DTs within the context of greenhouse horticulture.

Current applications of DTs in agriculture involve remote execution, monitoring, control, and coordination of farming operations, separating physical and information aspects (Verdouw et al., 2021). These virtual representations integrate data from diverse sources, including sensors and satellites, enabling advanced analytics and simulation of future behaviour. Consequently, DTs provide real-time insights and facilitate prompt action for expected or unexpected deviations (Verdouw et al., 2021). Furthermore, DTs in agriculture facilitate the testing of strategies for growers, including evaluating the trade-off between potential savings and risk, as well as participation in energy flexibility markets (Nasirahmadi & Hensel, 2022). However, the technology's implementation within an agricultural setting faces challenges in capturing dynamic behaviour, ensuring data integrity and security in rural areas, managing interdependencies, enabling secure external access, and achieving interoperability (Verdouw et al., 2021). Consequently, due to these challenges, the widespread implementation of DTs in agriculture is still within its infancy, with limited studies conducted and potential

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benefits yet to be fully realized, unlike in other domains (Pylianidis et al., 2021).

For DTs within the agriculture domain, in order to deal with the dynamic behaviour and enable advanced analytics and simulation of future behaviour high-fidelity, the modelling process is essential. More specifically, physical modelling (involving the creations of detailed representations of real-world objects) can provide insights which can be used for understanding and analysis of dynamic behaviour of the physical objects in agriculture domain that rather than data driven modelling (Liu et al., 2021). Liu et al. (2021) argue that physical modelling, as opposed to data-driven modelling, can offer valuable insights for comprehending and analysing the dynamic behaviour of agricultural objects. Within this setting, data-driven models are trained by known inputs and outputs, using artificial intelligence methods which make them only valid for those specific inputs and without giving the opportunity of biological explanation of the prediction. Whereas physical models require comprehensive understanding of the physical properties and their mutual interaction. Specifically, crop modelling pursues three primary objectives: (1) enhancing the cognitive capacity of the human brain through the integration of existing knowledge, (2) extrapolating the effects of factors beyond the range of experimentation, and (3) enabling practical management decisions, such as climate and nutrient control in greenhouse settings (Evers et al., 2005). Thus, computational models used in both inference of the physical object's current state and simulation can provide decision-making insights, optimizing future operations, forecasting degradation mechanisms, and predicting failures (Segovia & Garcia-Alfaro, 2022).

Crop modelling in plant sciences can either be process-based models that take into account the functionality, omitting the structural aspect of the plants or functional structural plant models that concern the structural aspect also. Further, Process-Based Models (PBMs) (Buck-Sorlin, 2013) focus on eco-physiological processes, for example nutrient absorption, light harvesting, photosynthesis, carbon assimilation, distribution, etc., for plant growth. Classical PBM addresses the implementation and simulation of the plant growth processes (e.g., Photosynthesis, C-N assimilation, and allocation) at the whole plant canopy level rather than individual plant organs level. Since PBM does not focus on the plant's architecture, it does not consider the interactions between plant growth processes and architecture development as per changing environment (de Reffye et al., 1997). To address this issue, Functional Structural Plant (FSP) models, also called virtual plant models, depict the dynamic 3D architecture of plants as influenced by physiological processes and environmental factors (Prusinkiewicz & Lindenmayer, 1990; Sievänen et al., 2000; Godin & Sinoquet, 2005; Vos et al., 2007; Hanan & Prusinkiewicz, 2008). The FSP modelling process is a valuable tool for scientists seeking to comprehend and address the dynamic behaviour of plants. These models are computer simulations that represent the three-dimensional (3D) architecture of plants. By simulating the plant's 3D structure, FSPM provide essential insights into plant parameters and their growth patterns (Patil et al., 2023). To that end, incorporating FSP modelling can enhance prediction accuracy of a DT and facilitate the assessment and creation of pruning strategies, enabling education of growers or guiding pruning robots. In addition, FSPM have practical applications in optimizing spraying techniques and can contribute to the construction of a more realistic dataset by incorporating environmental conditions, ultimately enhancing the estimation of light interception. Furthermore, its suitability for precision agriculture lies in its ability to accurately model the specific requirements and physiology of individual plants.

Consequently, plant modelling is essential for the creation of DT in agriculture to exploit their potential. In the existed explorative studies and cases about DTs in agriculture (Verdouw & Kruize, 2017; Jo et al., 2018; Monteiro et al., 2018; Kampker et al., 2019; Sreedevi & Santosh Kumar, 2020; Skobelev et al., 2020), plant modelling is barely used in the fundamental form of it while FSPM is not introduced. Thus, this article's contribution to knowledge is an analysis of how FSPM can be

integrated in DTs. More specifically, the objective is to propose a conceptual framework (*i.e.*, a systematic classification of concepts) for implementing FSPM in 3D-based DTs, where (as demonstrated in Section 2) there is a significant knowledge gap.

The remainder of this paper is as follows. A background on DTs and FSPM is provided in Section 2 and Section 3 outlines the search protocol and methodology used for the investigation. The domain analysis in Section 4 defines work that has been done in the domain of 3D plant phenotyping and 3D plant reconstruction, and how this can be interpreted in L-system formalism. Section 5 describes the conceptual framework developed, which comprises the main framework of integrating FSPM into DTs by relying in work that has be done already and the individual steps to achieve that. The main findings are summarized and discussed in Section 6 as well as, challenges and future work. Section 7 concludes the paper.

## 2. 3D plant modelling and DT in agriculture

## 2.1. DT in agriculture

#### 2.1.1. Type of DTs and terminology

According to Verdouw et al. (2021), there are six distinct types of DTs that are classified based on their specific objectives. These types include Imaginary, Monitoring, Predictive, Prescriptive, Autonomous, and Recollection DTs. Verdouw et al. (2021) also proposed a conceptual framework that takes into consideration variations in architecture and incorporates different layers, which become increasingly complex as one progresses towards an autonomous DT. Furthermore, this led to the development of a control model based on a general systems approach, as well as an implementation model that presents a comprehensive technical architecture for implementing DTs. For a more software engineering-oriented perspective, Tekinerdogan & Verdouw (2020) introduced a set of DT architecture design patterns that can be utilized to design systems catering to the requirements of each DT type. These patterns are formulated using the well-recognized context-problem--solution template for pattern formulation. The terminology used to describe the components of DTs (Appendix A) in the study in this article was derived from Jones et al. (2020), who conducted a systematic literature review to establish a standardized set of terminology for the field

#### 2.1.2. Control model in DTs in agriculture

DTs offer users the capability to disentangle the physical operations of agricultural farms from the information-related aspects (Verdouw & Kruize, 2017). In order to decouple the management of agricultural operations for users, the proposed control model framework by Verdouw et al. (2021) was designed to convert data collected from the physical systems of farms into a DT representation (Fig. 1). This control model is structured into six layers, each orchestrating functions contributing to the establishment of the DT and enabling seamless communication between its physical and digital counterparts. Initiating the control cycle, the state of the object is perceived through the data function, which is responsible for measuring the state of an object using sensors or external data sources such as satellites and weather databases. The data collected by the data function is then input into models within the meta model function. These models, which can be data-driven, functional, or process-based, or a combination, are instrumental in generating the DT representation. However, solely representing the current state of the object is insufficient for farmers. Therefore, an additional meta model function can take the object's current state as a starting point, utilizing predictive models to forecast future states. Subsequently, these projected future states are assessed by the application function. Within the application function, scenarios derived from the meta models are compared with established norms, and the optimal scenario is selected for implementation. Once the best scenario has been identified, the decision maker function within the application layer determines how

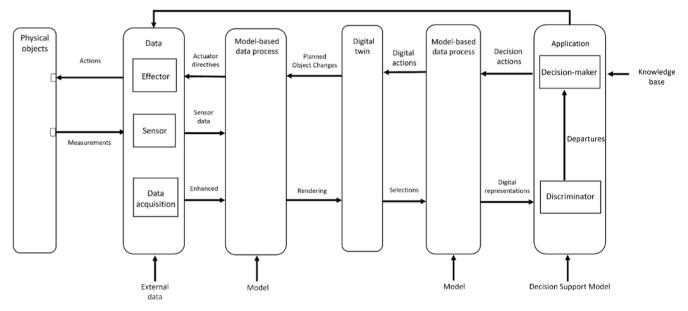


Fig. 1. Conceptual model for DTs, based on Verdouw et al. (2015). Rectangles denote the functions encapsulated within the layers, denoted by orthogonal symbols, while arrows delineate the flow of information.

the subsequent management actions will be executed. The effector function in the data layer receives instructions from the application layer regarding the changes to be made in cultivation management. This constitutes a single cycle, and it will be reiterated over time, dependent on the DT's time step. In the control model, data from the data layer is directed towards the model-based data processing phase. This process employs various models to analyse the data and generate the DT. This process ensures the communication of the physical twin with the digital and the opposite and keep informed each other. As previously mentioned in the introduction, FSPM holds a significant advantage in translating the data, enabling the creation of a DT that not only represents the 3D architecture of the physical twin but also its functionality. It is imperative to acknowledge that the illustrations provided represent only the overarching layers and their interconnections, while the internal structures within each layer are considerably more intricate (Appendix A). In the scope of this research, particular emphasis will be placed on expanding the model-based data processing layer and proposing a framework for the integration of FSPM in it. Furthermore, the development of this framework necessitates comprehensive consideration of all layers to ensure seamless communication in real-time or near real-time for the effective operation of the DT. Therefore, an examination of each layer was essential in formulating the framework.

#### 2.2. Functional structural plant modelling

FSPMs incorporate physiological processes influenced by environmental factors, allowing for the study of plant responses to various environmental conditions and the influence of different traits on plant performance. By employing mathematical algorithms, FSPMs offer valuable insights into plant growth patterns, resource allocation, and interactions with the environment, enabling scientists to understand and predict plant behaviour in diverse scenarios. Since their inception, one of the primary objectives of FSPMs has been to develop predictive models in applied domains where plant architecture plays a critical role, such as modelling plant growth in spatially heterogeneous environments (e.g., understorey, greenhouses), assessing competition in plant communities, studying selective canopy perturbations (e.g., herbivory, pruning), and defining ideotypes for breeders (Louarn & Song, 2020).

In FSPMs, plants are represented as interconnected units called phytomers or metamers, each comprising an internode, a node, and a leaf. The plant architecture is described using L-system strings

(Prusinkiewicz & Lindenmayer, 1990), which employ a rewriting technique to progressively transform a simple initial object into a complex structure through productions, also known as rules. Later, Kurth et al. (2004) introduced relational growth grammars (RGG) as an extension of the L-system, enabling the incorporation of non-linear relationships in architectural modelling. Turtle geometry (Abelson & DiSessa, 1986) is then employed to interpret L-systems and RGG for graphical purposes. FSPMs capture the adaptive nature of plants, as they modify their functions, such as photosynthesis, transpiration, and nitrogen allocation, as well as adjust their structure in response to environmental cues, including bud breakage, dormancy maintenance, and organ shape and orientation adjustments. This reciprocal relationship between structure and function is explicitly captured in FSPMs, allowing for the representation of feedback loops. These feedback can be examined at both the local level, involving individual organs, and the global level, encompassing the functioning of the entire plant or plant stand. Key topics in FSPM research include models of morphological development, models of physical and biological processes, integrated models predicting the dynamics of plants and plant communities, modelling platforms, methods for acquiring 3D plant structures using automated measurements, and practical applications in agronomy (Sievänen et al., 2014). Despite making significant strides in plant science over the past two decades, FSPMs have yet to fulfil their full potential (Louarn and Song, 2020).

# 2.2.1. Plant topology and geometry

In the field of FSPM, the plant architecture is described using the concepts of topology and geometry. Topology pertains to the physical connections among various components of the plant, while geometry encompasses the characteristics such as shape, size, orientation, and spatial location of these components (Godin et al., 1999). The initial step in constructing a structural model involves identifying the different types of plant organs that can be formed and understanding their connections, *i.e.*, the topology. It is important to note that the interconnections between organs can vary depending on the plant species. For more complex tree architectures, a multigraph tree model is employed. The topology of a tree is described using the multiscale tree graph formalism (Godin & Caraglio, 1998), which accounts for different levels of organization (Barthélémy, 1991) and captures plant structure by incorporating associated variables like geometrical measurements and phenological data. Multiscale tree graph formalism provides a

suitable means for representing tree-like topologies concisely, considering aspects of scale and time.

#### 2.2.2. Platform and software of FSPM

Several FSPM methods have been developed, with L-Studio being one of the pioneers (Allen et al., 2007). L-Studio is based on the L-system formalism (Lindenmayer, 1968; Prusinkiewicz et al., 1996) and utilizes the modelling language L + C (Prusinkiewicz et al., 2007). Another increasingly used platform is GroIMP, which is based on RGG and employs the modelling language XL (Kniemeyer, 2007). Zhou et al. (2020) introduced CPlantBox, a Python-based whole-plant functional-structural modelling framework that simulates both root and plant shoot structures. Barczi et al. (2008) proposed AMAPsim, a structural whole-plant architecture simulator written in C++, which combines architectural and physiological models. The GreenLab mathematical model (de Reffye et al., 2021), integrates functional and structural aspects of metabolic processes with a phytomere-level structure. These models contribute to the advancement of FSPM methodologies, providing researchers with diverse platforms and models for investigating plant development and the interplay between functional and structural aspects.

#### 2.2.3. FSPM applications

FSPM serves not only as a tool for scientists to test hypotheses and conduct in silico experiments that are difficult to replicate in reality but also finds practical applications in the field of agronomy. FSPM can help on assessing how plant traits affecting light interception and consequently processes like photosynthesis. Zhang et al. (2020) conducted a quantitative investigation to explore the effects of different architectural traits and canopy management on light interception and potential carbon accumulation. Similarly, Prieto et al. (2020) employed a comparable approach in grapevine research, comparing photosynthetic gains achieved by different training systems, including scenarios with free shoots exhibiting complex architecture. Moreover, FSPM can be used for optimization of management of the crop, such as spraying. Gu et al. (2014) developed an FSPM for cotton that considered factors, such as thermal time, population density, mepiquat chloride application, and stem and branch topping. Simulation results indicated that mepiquat chloride application reduced leaf area and internode length, resulting in a more compact canopy, while having negligible effects on boll density.

The integration of FSPMs with AI holds great potential in the fields of breeding and advanced phenotyping. Ubbens et al. (2018), for example, employed a computer-generated model of Arabidopsis rosettes to enhance leaf counting accuracy using convolutional neural networks. By incorporating synthetic rosettes in conjunction with real training data, they achieved a reduction in mean absolute count error compared to

previous methods that exclusively utilized real plant images. Notably, interoperability experiments demonstrated that a convolutional neural networks trained solely on synthetic rosettes successfully counted leaves in real rosettes. Additionally, Liu et al. (2017) focused on estimating the green area index of wheat through ground-based LiDAR measurements, utilizing a 3D canopy structure model. The utilization of 3D plant models proves to be beneficial in training neural networks for image-based plant phenotyping applications.

# 2.2.4. FSP models workflow

Considering the diverse range of FSPMs employed in different contexts and for various crops and objectives, development of a general FSPM, which can then be modified by adapting its modules to specific crops and objectives is beneficial (Henke et al., 2016). The study by Henke et al. (2016) presents an initial step towards establishing a general FSPM with standardized modules, processes, and communication structure. This approach facilitates a clear and well-defined model design that is easily parametrized, comprehensible, and expandable. This generic FSPM comprises an initialization function init(), responsible for initializing the plants (Axiom, *i.e.*, the initial plant architecture), parameters, and environmental conditions (Fig. 2).

Subsequently, in the run() function, the model executes growth functions and assimilate allocation, applies relevant rules, and considers the environmental factors. This represents the main loop, where the model updates the plant state at each time step using ordinary differential equations (ODEs). At each iteration, the stop() function checks if the plant has reached the end of its life cycle. If not, the model continues within the main loop. For further details on the specific functionality of each function, readers are referred to the work by Henke et al. (2016).

#### 3. Domain analysis protocol

The research review process was organized in four phases: (i) DT domain analysis, (ii) Functional structural plant modelling domain analysis (iii) 3D plant reconstruction domain analysis and (iv) framework design. Initially, a domain analysis was conducted in the field of DTs to gather existing terminology from previous research. This step aimed to ensure consistency in the use of terminology throughout the study, thereby avoiding potential confusion caused by employing different terms. Subsequently, a domain analysis has reviewed existing literature on the usage of DTs in the context of agriculture and the role of FSPM. At this, the search focused on articles that involved both DT and agriculture or farming in the title, abstract or the keywords section. Non-English and non-accessible papers were excluded from the study. Then, the search was extended to include FSPM and 3D reconstruction of

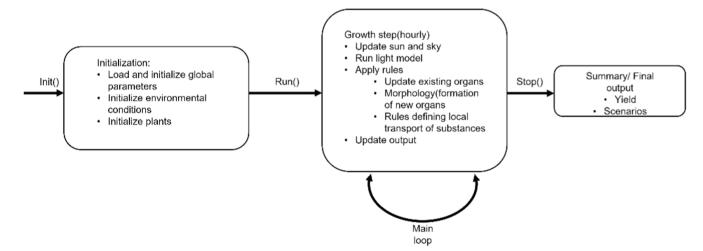


Fig. 2. Functional structural plant model workflow adapted from Henke et al. (2016)

plants. Based on this domain analysis, a conceptual framework on how functional structural plant modelling can be integrating into DT concept was provided. Connecting all the information from the background research on this topic a framework on how a single physical object (*i.e.*, plant) can be transformed into the digital object for a DT.

#### 3.1. Search queries

The search queries were utilized to gather information within the analysis domain for the research study (Table 1). The resulting papers from these search queries were then subjected to forward and backward snowballing techniques. This involved examining the references cited within the papers (backward snowballing) as well as identifying newer papers that have cited the original papers (forward snowballing). After conducting the snowballing process, all the collected papers were screened, and the full texts of the remaining papers were assessed. Finally, based on this screening and assessment, the articles that met the inclusion criteria were selected for the study (Fig. 4).

#### 3.1.1. Research questions

In order to address the primary objective of this research, three distinct research questions were formulated to yield relevant information and valuable insights regarding the approach to be undertaken in developing a conceptual framework for integrating FSPM into DTs within the domain of agriculture. The subsequent research questions were defined:

- 1) To what extent has plant and 3D plant modelling been employed to develop DT applications in agriculture?
- 2) How has the physical object been perceived and reconstructed in existing literature?
- 3) How can FSPM be used to support the creation of 3D DTs for agriculture?

To answer the aforementioned research questions, a domain analysis was performed by focusing on the Scopus digital library, with the search strings displayed in Table 1. As mentioned, articles relevant for this study but not included in Scopus were identified by means of snow-balling. The time period for article inclusion encompassed all available literature, except for studies specifically related to DTs, which were restricted to the period from 2017 onwards. This approach was adopted to ensure comprehensive coverage of the FSPM and 3D plant phenotyping domains, which have been established for over two decades. By not excluding articles from these domains, we aimed to avoid overlooking important contributions to the field.

**Table 1**Search queries for the different domain analysis.

Database	Domain analysis	Search string
Scopus	DTs in agriculture	("digital twins" OR "Cyber- physical system" OR "emulation" OR "Simulation") AND ("plant model*") AND ("agriculture" OR "farm*")
Scopus	Functional structural plant modelling domain analysis	("FSPM" AND "Plant")
Scopus	3d plant reconstruction and phenotyping domain analysis	("3d plant representation" OR " plant rendering" OR "3d plant reconstruction" OR "skeletonization") AND ("Plant" OR "agriculture" OR "leaf" OR "plant structure" OR "skeleton") AND ("segmentation" OR "machine learning" OR "computer vision" OR "artificial intelligence")

#### 3.2. Selection criteria

The selection process involved filtering the search query results based on predetermined selection criteria outlined in (Table 2). Only articles deemed relevant to the study's objectives were chosen. The collection of articles was obtained from Scopus database using the research string and the snowball method to enhance the retrieval process. Subsequently, data pertinent to the study, extracted exclusively from the articles meeting the selection criteria, were compiled and presented in (Table 3).

#### 4. Domain analysis

#### 4.1. 3D plant modelling for DT applications in agriculture

Although a conceptual framework for DTs in agriculture exists, the practical implementation falls short of its theoretical potential. Literature review indicates that most DTs developed in the agricultural domain are primarily focused on monitoring (Fig. 4). While Chaux et al. (2021) proposed a complete architecture for DT s in controlled environments like greenhouses, it remained generic without detailed explanations or real case studies for workflow optimization. Two studies. such as Ahmed et al. (2019) and Skobelev et al. (2020), utilized process models and knowledge-based models and presented a framework utilizing knowledge-based modelling to develop DT of plants. However, none of these studies were able to provide predictive capabilities or effectively evaluate different scenarios. Others, like Ahmed et al. (2019) and Jans-Singh et al. (2020), concentrated on modelling aspects and the use of meta models to facilitate DT implementation. These studies explored modelling techniques and meta model approaches to enhance functionality. Pylianidis et al. (2022) introduced a method for developing operational DTs that addressed data availability and resolution challenges. They demonstrated the method's effectiveness in nonlinear scenarios, providing tactical advice for grass pasture nitrogen response rate across different locations.

However, none of the reviewed articles (Fig. 4) showcased autonomous behaviour or an intelligent layer capable of learning and making independent decisions for crop management optimization.

Most existing agricultural DTs primarily concentrate on the sensor layer and data storage aspects, lacking the incorporation of functional 3D plant models. Only one study, namely Jans-Singh et al. (2020), included 3D representations of the control environment and plants; however, it did not encompass the exact physical objects themselves. While a few studies briefly mentioned certain layers, such as Alves et al. (2019) and Chaux et al. (2021), they lacked sufficient details on their creation and derivation. Some studies, like Hemming et al. (2020) and Howard et al. (2020), did not elaborate on the machine learning algorithms used or how each layer could be implemented. Overall, there is a need for a proposed conceptual framework that integrates a 3D plant model of the physical object with functional capabilities, addressing the limitations and gaps identified in the existing literature. While 3D plant modelling has been utilized predominantly for non-existing plants, the application of this technique to physical objects and the creation of DTs requires 3D plant phenotyping to be performed.

# 4.2. Physical object reconstruction

Accurate representation of physical objects in DTs necessitates the inclusion of 3D plant phenotyping. The ability to access and analyse the plant architecture plays a crucial role in monitoring the geometric development of plants and parameterizing various aspects, such as plant canopies, individual plants, and plant organs (Godin, 2000). Obtaining accurate and timely measurements of phenotypic traits, such as in tomato canopies is of significant importance for purposes such as variety breeding, cultivation, and scientific management. However, the traditional approach of manual measurements is burdensome, time-

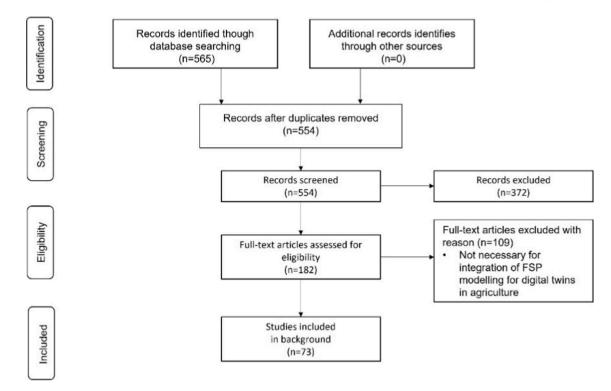


Fig. 3. Literature review methodology diagram.

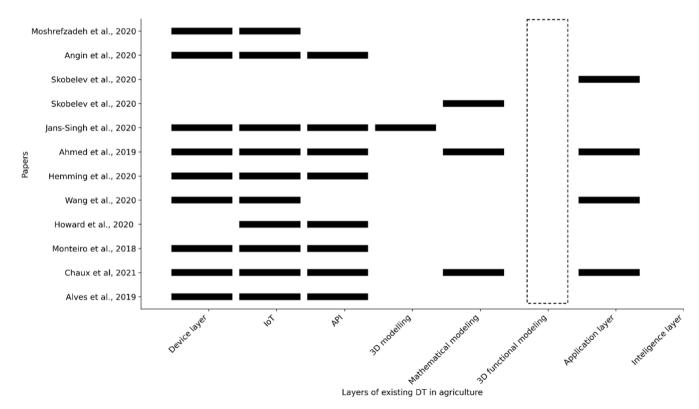


Fig. 4. Composition of layers of existing DTs in agriculture domain. Dotted line indicates non-existent DTs with 3D functional modelling. (Ahmed et al., 2019; Alves et al., 2019; Angin et al., 2020; Howard et al., 2020; Chaux et al., 2021, Hemming et al., 2020; Moshrezadeh et al., 2020).

consuming, and prone to errors (Zhu et al., 2023). In recent years, several studies have focused on plant phenotyping using 3D sensing technologies (Paturkar et al., 2021; Paulus, 2019; Liu et al., 2020). The non-destructive nature of 3D measuring allows for continuous monitoring over time, offering new possibilities in understanding plant

growth dynamics (Paulus et al., 2014). These phenotypic traits, including leaf area index, plant biomass, plant density, chlorophyll content, and crown temperature, serve various biological purposes, for instance, in stress detection (Feng et al., 2021). In this regard, non-destructive phenotyping techniques can be leveraged to develop DTs

Table 2
Selection criteria of the study.

#### Exclusion criteria

Articles without full text available
Articles not written in English
Duplicate publication
Publications that are not articles (e.g., survey)
Articles do not associate to DT within agricultural domain
Articles do not associate with FSPM
Articles do not associate with 3D plant phenotyping
The articles related to DT were published before 2017

**Table 3**Data extraction for the study.

Data per Article

Authors

Title

Year of publication

Process for creation of DT within agriculture domain

Process for 3D plant phenotyping

Data used for 3D plant phenotyping

Algorithms or models used for transformation of 3D plant reconstruction into L-system and RGG

What Machine learning were implemented for 3D plant phenotyping

FSPM workflow

that facilitate disease analysis, stress detection, and other applications.

#### 4.2.1. 3D measuring technologies

Various 3D sensing technologies (Table 4) are available for plant reconstruction (Paturkar et al., 2021). Paulus (2019) conducted a comprehensive survey on acquisition techniques, representations, and analysis methods for 3D plant physiognomic analysis. Moreover, different sensors, including RGB cameras, multispectral/hyperspectral cameras, and thermal cameras, are used to extract various plant traits such as size, shape, colour, stress detection, and temperature variations (Minervini et al., 2015; Rumpf et al., 2010; Mahlein, 2016; Jones et al., 2009). Liu et al. (2020) provide a review of the spectrum of technologies used in plant phenotyping, highlighting the increasing interest in hyperspectral imaging (HSI) and 3D sensing. LiDAR and Structure from Motion are the dominant 3D sensing technologies used (Liu et al., 2020). However, accurate 3D modelling of plants remains a challenge, especially for narrowleaf plants. The fusion of hyperspectral and 3D data showed potential for improving plant phenotyping capabilities (Liu et al., 2020).

#### 4.2.2. 3d plant reconstruction

The representation of 3D plant architecture in computer graphics is of clear significance for the creation of DTs. Li et al. (2022) proposed a method for reconstructing 3D leaves using a single view, utilizing the fusion of ResNet and differentiable rendering. Their approach focuses on incorporating individual leaves into a plant growth DT system, rather than reconstructing the entire plant. However, their study only focused on a single leaf. Le Louëdec & Cielniak (2021) constructed strawberry plants in the Unity software platform, testing two different 3D technologies. For woody species reconstruction, Lau et al. (2018) derived the skeleton of trees from point cloud data. However, these algorithms

provided the skeleton of the plant without considering the leaf area. Further research on skeletonization considering plant leaves is worth exploring to accurately reconstruct the geometry of leafy plants (Chaudhury et al., 2020). Cuevas-Velasquez et al. (2020) presented a 3D reconstruction method for rose bushes using stereo images, integrated into a robotic system for automated pruning. Their segmentation approach achieved a superior F1 score of 77 %, outperforming state-of-the-art methods by 8.18 %.

Automated 3D reconstruction of plants is crucial for DT applications. Various studies have focused on automatic reconstruction methods for plant architecture using laser scanner data or high-resolution scans of plants. These methods aim to achieve accurate plant reconstruction without relying on manual intervention or the need for a branching pattern. Examples include the work of Boudon et al. (2014), Japes et al. (2018), and Guénard et al. (2013), which explored different approaches for automated plant modelling and reconstruction using advanced techniques such as analysis, synthesis, and semantic labelling of 3D point clouds. Paproki et al. (2011) automated the reconstruction of cotton plants. Moreover, Xiang et al. (2019) developed a cost-effective machine vision system that utilized a commodity depth camera to capture sequential side-view images of sorghum plants at different growth stages. Their system accurately detected individual leaves and distinguished tillers using 3D point cloud analysis. However, 3D plant reconstruction provides the architecture without having the functionality that FSPM can provide.

#### 4.2.3. Plant phenotyping traits and process pipeline for phenotyping traits

After obtaining the raw data, typically in the form of a point cloud, from one of the aforementioned 3D sensing technologies, a processing pipeline can be employed to extract different types of plant traits, including non-complex traits, complex traits, and time-lapse traits (Fig. 5). Focusing on specific areas of interest and removing outliers can facilitate the calculation of straightforward attributes like plant height and leaf length. For more complex attributes, such as organ biomass, advanced ML techniques like classification, deep learning, and clustering can be employed. Additionally, when time-series data is accessible, ML algorithms can be used to determine attributes like the relative growth rate of leaves. Ultimately, obtaining a 3D mesh and creating a reconstructed rendering of the plant is essential. In this process, rendering is integral to deriving parameters through the analysis of diverse meshes.

However, the accuracy and complexity of these parameters depend on the specific procedures employed. For instance, Zhu et al. (2023) reconstructed a tomato canopy model and achieved high accuracy in estimating plant height, canopy width, and leafstalk angle. The accuracy rates were reported as 96.23 %, 95.17 %, and 91.76 %, respectively. In the case of complex traits, Masuda (2021) aimed to estimate the leaf area of tomato plants using an RGB-D sensor and semantic segmentation in a sunlight-type plant factory. By applying Pointnet++ for semantic segmentation and estimating leaf area based on the leaf points around the stem, they achieved a relative error of approximately 20 %, comparable to simplified non-destructive methods commonly used in cultivation sites. However, the limited availability of ground truth data was a constraint in the study. Lati et al. (2013) developed a 3D stereovision model for accurate estimation of spatial growth measurements, including biomass, in plants. Their model utilized a global optimization method and ensured high confidence matching of corresponding points.

**Table 4**3D measuring technologies .

3D measuring Techni	ques					
Active				Passive		
Triangulation		Time-of-Flight		Structure for motion	Stereo Vision	Light Field
Structured light	Laser Triangulation	Time-of-Flight camera	Lidar			

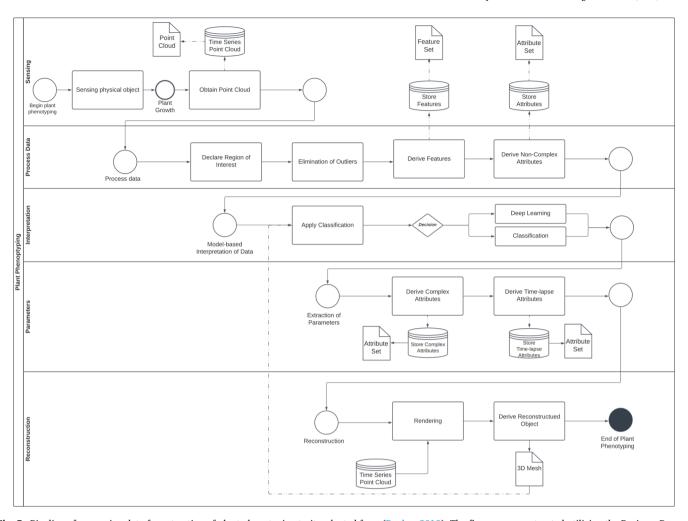


Fig. 5. Pipeline of processing data for extraction of plant phenotyping traits adapted from (Paulus, 2019). The figure was constructed utilizing the Business Process Model and Notation (BPMN) 2.0 framework, as outlined by Chinosi & Trombetta (2012).

By incorporating processing adjustments, such as parallel computing, the algorithm could be applied in real-time scenarios. It should be noted that plant phenotyping varies at different levels, and while the above research focused on individual plants.

The architecture of trees presents greater complexity. For instance, Lau et al. (2018) assessed the accuracy of using Terrestrial Laser Scanning and TreeQSM to reconstruct tree architecture parameters in tropical trees, such as branch length, branch diameter, branching order, and tree volume. To address the time-consuming and manual-intensive nature of plant 3D data processing techniques, Ghahremani et al. (2021) proposed a method to directly utilize irregular point clouds for measuring organ attributes in plant phenotyping, effectively handling noise, distortions, and irrelevant data. Additionally, Li et al. (2022) presented DeepSeg3DMaize, an automatic 3D point cloud segmentation method for maize plants. By leveraging high-throughput data acquisition and deep neural networks, accurate segmentation of maize plants was achieved at different growth stages, heights, and leaf numbers.

Time-lapse point cloud analysis offers valuable insights into plant growth and various traits over time (Fig. 5). Automation plays a crucial role in integrating these analyses into DT systems. For instance, Paulus et al. (2014) developed an automated approach to track the organs (leaves and stems) of barley plants over time. By combining surface feature histograms with parametric modelling, the method facilitates the calculation of parameters, such as cumulated height for the stem and cumulated leaf area. Chebrolu et al. (2021) introduced an automated method for tracking plant traits over time, eliminating the need for manual intervention. Through alignment and transformation of 3D

scans, this approach enables the estimation of parameters like leaf area, leaf length, stem diameter, and stem length, contributing to automated phenotyping. Such automation allows for efficient monitoring of plant development over time. Rincón et al. (2022) demonstrated the use of low-density vertical LiDAR radars and multispectral images to examine morphological changes and analyse variables and physiological parameters under different environmental conditions. However, it is important to ensure compatibility between the physiological traits and plant modelling for DT applications. Kattenborn et al. (2022) presented AngleCam, a convolutional neural network based method that utilizes low-cost outdoor cameras to estimate leaf angles from horizontal plant photographs. The estimated angles, along with their derivatives, can be applied in various applications, including FSPM. Magistri et al. (2020) introduced a novel approach for tomato and maize plants, which exhibited superior performance compared to existing techniques. Their approach improves data association between point clouds of plants at different growth stages, enabling the computation of multiple phenotypic traits at each time point.

# 4.3. Use of FSP modelling to support the creation of 3D DTs for agriculture

Reconstruction involves creating plant shapes or structures that resemble existing plants, while modelling focuses on simulating the shapes and structures of non-existent plants. Okura (2022) discussed the trends in 3D modelling and reconstruction of plants and trees. However, the review did not touch upon the integration of 3D plant phenotyping

into FSPM. This integration between FSPM and 3D reconstruction has the potential to enhance both fields. Specifically, the integration can improve mathematical biological modelling by allowing for more precise calculation of parameters, and it can provide a scientific basis for generating more realistic plants in FSPM. There are several reasons for adopting such an approach. Namely, from a theoretical perspective, scientific data exists at multiple scales, and integrating this data can improve model accuracy. From a practical standpoint, different scales of screening and monitoring, such as disease and yield estimation, can benefit from this integration (Schöler & Steinhage, 2015).

To achieve this, the outcomes from 3D phenotyping need to be compatible with the inputs of FSPMs (as described in section 3.2). Regarding this, algorithms used for automatic identification of elementary units like nodes, internodes, foliage, buds, and cells can facilitate parameterization of FSPMs and allow for their assessment using accurate, real data (Boudon et al., 2014). Moreover, Schöler (2014) proposed a 3D reconstruction approach for plant architecture based on the interpretation of 3D laser scan point clouds. Their method incorporated intelligent sampling and domain knowledge to constrain the space of hypotheses. They used the Reversible Jump Markov Chain Monte Carlo method for sampling and RGG for modelling of the plants. They applied this approach to investigate stem skeletons of grapevine bunches and derived phenotypical features based on the reconstructed plants. Schöler & Steinhage (2015) developed an automated processing chain for reconstructing grape clusters using 3D point clouds from a laser range sensor. Their approach utilized a rule-based generative model to handle occlusions and objectively extract phenotypic traits. They suggested extending this model-based processing chain to other plant organs, whole plants, and different species. In a recent study, Hu et al. (2022) presented a framework for realistic 3D plant modelling and agricultural scene rendering. Their automated approach, based on dualfaced leaf model reconstruction, captured fine geometric details and estimated light properties. The leaf reconstruction process was automated, except for acquiring real leaves, enabling the creation of diverse agricultural vegetation scenes with high realism. This framework facilitated the generation of diverse agricultural scenes and improved weed detection algorithms. Future research directions include simultaneous reconstruction of reproductive organs and optical properties, as well as capturing plant development patterns for species-specific parametric Lsystems. Based on the advancements in both 3D reconstruction and FSPM, a conceptual framework for FSP modelling in DTs is proposed in the next section. The proposed framework builds upon the identified existing research in these two fields and aims to integrate their findings and methodologies.

# 5. Proposed framework

The general control model including FSPM can be the conceptual framework proposed showed the integration of the DT model with FSPM approaches and is plant agnostic. The operational process of the control model is outlined and structured into distinct steps (3D plant phenotyping, 3D Plant Reconstruction into L-System, FSPM, Parameterization and Model Update, Evaluation of Model Performance), elaborated as follows.

# 5.1. Control model operational process

#### A. 3D Plant Phenotyping

The initial step in integrating FSPMs into 3D DT entails 3D-based plant phenotyping. This process captures a plant's spatial structure using a point cloud derived from advanced imaging methods (discussed in section 4.2.1). This point cloud serves as the foundation for subsequent stages. Notably, the point cloud is segmented to isolate distinct plant components, enabling detailed analysis. A key outcome of this phase is the computation of a semantic skeleton, encapsulating the

plant's core structural framework. This skeletal representation simplifies the architecture while providing informative insights into spatial arrangement and branching patterns. This phase yields two main outputs: the semantic skeleton and crucial plant features like biomass, pivotal for comprehending plant behaviour and growth.

# B. 3D Plant Reconstruction into L-System

Output from the aforementioned step is utilized further to create a plant architecture described in L-system and RGG. Leveraging the semantic skeleton and the original point cloud, a sophisticated matching process commences. This process aims to find the best-fitting architectural model within an L-System and RGG using the RJMCMC algorithm. The outcome of this phase is the semantic skeleton undergoes translation into the L-System realm.

#### C. FSP Modelling

The plant architecture, transformed into L-system and RGG realm, is then incorporated as the axiom within the FSPM. This axiom serves as the initial state for the model's operation. The model operates in discrete time steps, simulating the plant's growth and interactions within its environment. The FSPM is executed to predict desired variables, such as yield under different scenarios. While the foundational function of an FSPM was discussed in section 2.2.4, it is notable that the FSPM embedded within the DT framework can undergo calibration as the crop's lifecycle progresses and as new data becomes available.

# D. Calibration and Model Update

Progressing chronologically, the proposed framework in this step initiates a calibration and model update iteration at each time step. Central to this iterative process is the pursuit of enhancement and refinement. A focal point of this endeavour is the introduction of a performance metric that seeks to mitigate disparities between model predictions and empirical observations. For instance, the Levenberg-Marquardt optimization technique (Moré, 2006) is employed as an illustrative example to adjust the model's parameters.

#### E. Evaluation of Model Performance

As the plant's journey approaches its conclusion, the FSPM directs its attention toward evaluating model performance. This phase reflecting how well the FSPM captures the essence of reality. Metrics take centre stage: the Bayesian Information Criterion (BIC) measures model complexity, the Root Mean Squared Error (RMSE) quantifies prediction errors, and the efficiency metric gauges the model's predictive capability.

This algorithm weaves together advanced techniques of 3D plant phenotyping, L-System reconstruction, FSP modelling, parameterization, and performance evaluation. Each phase contributes its unique threads to a tapestry that enhances a DTs' capability to simulate and predict the behaviours of plants within complex and dynamic environments.

# 5.2. 3D plant phenotyping

The operational process of 3D plant phenotyping unfolds in a systematic sequence of steps, each contributing to a comprehensive understanding of plant features and characteristics. To begin, the process involves gathering 3D plant model data, which is achieved either by reading data from a file or by capturing it directly using specialized 3D sensors. This initial dataset forms the foundational raw material for the subsequent analysis. Once the data is collected, the control model undertakes a refining phase. This step entails preprocessing the data to eliminate unwanted noise and outliers. By tidying up the dataset in this

manner, the model ensures that its subsequent operations are built upon a clean and accurate foundation. Moving forward, the segmentation phase comes into play. Here, the model delves into the intricate structure of the plant, effectively dividing it into discrete components such as leaves, stems, and flowers. This segmentation process leverages sophisticated algorithms that dissect the complex plant structure into its constituent parts. Having successfully identified the individual components, the model progresses to the quantification of phenotypic traits. This involves an in-depth analysis of each component, generating key measurements to characterize its attributes. These quantified traits encompass crucial aspects:

- Volume: The model computes the volume of each component through integration of its 3D shape.
- Surface Area: Estimation of the component's surface area is achieved by summing the areas of its constituent surface polygons.
- Length: In cases of stems or branches, the model calculates their lengths by aggregating the distances between consecutive points.
- Curvature: The model examines the curvature of the plant model, effectively identifying features such as leaf angles or points of bending.
- Width: Measurement of width, such as the diameter of branches or the width perpendicular to the length of leaves, contributes to a comprehensive characterization.

As the phenotypic traits are calculated, the model ensures their retention for future reference. This accumulation of data serves as a reservoir of insights for subsequent analysis or visualization purposes. The iterative nature of the framework is evident as the control model proceeds to journey through multiple time points, effectively mirroring the plant's lifecycle. This repetition is instrumental in capturing the evolution of the plant's traits over time, allowing for a dynamic understanding of its characteristics. With the phenotypic insights accumulated, the model shifts its focus to visualization. This final step involves the transformation of data into understandable forms. Visualizations, such as graphs, charts, and immersive 3D representations, are deployed to convey the intricacies of the plant's story to a wider audience, bridging the gap between raw data and meaningful understanding.

In essence, the control model orchestrates an intricate dance of data collection, refinement, segmentation, quantification, retention, and visualization. Each step seamlessly connects to the next, culminating in a holistic process that sheds light on the rich world of plant characteristics and behaviour. The pseudocode in Algorithm 1 provides a general framework for 3D plant phenotyping. The specific implementation details will depend on the software or programming language you are using and the available libraries for point cloud/mesh processing and segmentation.

Algorithm 1. General process of 3d plant phenotyping

- 1: **Read** 3D plant model data (e.g., point cloud or mesh) **from** a file or capture it using a 3D sensor.
- 2: Preprocess the plant model data to remove noise and outliers.
- 3: **Segment** the plant model into individual components (e.g., leaves, stems, flowers) using segmentation algorithms.
- 4: Calculate various phenotypic traits for each component, such as:

Volume: Compute the volume of each component by integrating the 3D shape.

Surface Area: Estimate the surface area of each component by summing the areas of its surface polygons.

Length: Measure the length of stems or branches by summing the distances between consecutive points.

Curvature: Analyze the curvature of the plant model to detect features like leaf angles or bending.

Width: Estimate the width of branches or leaves by measuring the diameter or width perpendicular to the length.

- 5: **Store** the calculated phenotypic traits for further analysis or visualization.
- 6: **Repeat** the above steps for multiple time points till the end of lifecycle of the product.
- 7: **Visualize** the phenotypic data using appropriate graphs, charts, or 3D visualizations.

#### 5.3. 3D plant reconstruction into L-system

The process of translating the point cloud delineating the physical twin into L-system architecture poses a formidable challenge within the framework. Below is a delineation of the sequential steps essential for accomplishing this task. The FSPM's axiom is initialized based on the reconstructed tree architecture obtained from computer vision techniques, discussed in Section 4.4. To accomplish this objective, a point cloud is obtained using the methodologies outlined in Section 4.2.1. Subsequently, an algorithm, (Schöler et al., 2013; Lau et al., 2018; Du et al., 2019), should be employed. This algorithm is tasked with translating the point cloud into an L-system, ensuring the inclusion of the appropriate attributes such as length, internode, and radius, thereby facilitating the creation of the tree architecture (Fig. 6).

For the comprehensive illustration of this step in this framework, the proposed Algorithm 3 employs a RJMCMC (Green, 1995) approach augmented with simulated annealing (Geyer & Thompson, 1995) to optimize L-system architectures for accurately representing plant structures based on observed point cloud data. At the heart of the algorithm lies the Metropolis-Hastings framework (Chib & Jeliazkov, 2001), wherein candidate L-system states are stochastically generated through random perturbations from the current state. These perturbations serve to explore the solution space by proposing alterations in the L-system parameters, which define the structure of the simulated plant. The acceptance of proposed changes is determined probabilistically, allowing for the exploration of potentially suboptimal solutions to avoid local minima. Simulated annealing is employed to control the exploration-exploitation trade-off by gradually reducing the temperature parameter over the course of iterations. This gradual cooling schedule enables the algorithm to initially explore a wide range of solutions with higher acceptance probabilities and subsequently focus on refining promising regions as the temperature decreases. The effectiveness of the algorithm in discovering optimal L-system architectures is demonstrated through iterative refinement towards maximizing the fitness score, indicative of the resemblance between the generated plant structures and the observed point cloud data. Algorithm 2 does not explicitly address the specific challenges, for example, related to handling occlusions that are commonly encountered in the process. However, Schöler & Steinhage (2015) have extensively covered this aspect in their work, where they developed an automated processing chain utilizing a rulebased generative model to address occlusions when reconstructing grape clusters from 3D point clouds obtained from a laser range sensor.

It is imperative to underscore that within the domain of point cloud translation into L-systems, a plethora of methodologies are available in the extant literature, subject to continuous and intensive research efforts. Notably, prominent among these methods are TreeQSM (Lau et al., 2018) and AdTree (Du et al., 2019), both renowned for their efficacy in accurately transforming tree skeletons into L-system representations. However, a notable challenge persists in adequately capturing leaves and fruits through these algorithms, necessitating the exploration of alternative approaches. Recently, a pioneering method proposed by Wang et al. (2023) has emerged for the reconstruction of trees from incomplete point cloud data, exhibiting superior accuracy compared to its predecessors. Furthermore, the integration of a Convolutional Neural Network (CNN) coupled with Long Short-Term Memory (LSTM) architecture (Magnusson et al., 2023), offers a promising avenue for expeditiously translating images depicting tree topologies corresponding L-system representations. This advancement holds significant utility, particularly in facilitating the rapid translation of entire L-system architectures from reconstructions of 3D plant architectures, a

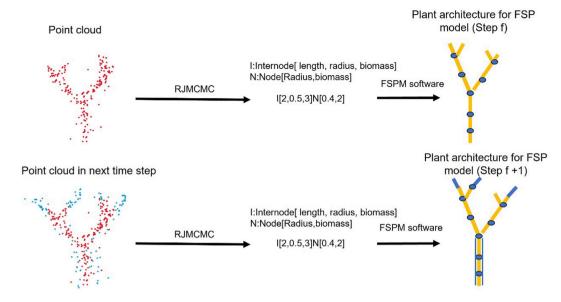


Fig. 6. Translation of 3d point cloud to 3d architecture in L-system and relation growth grammars.

#### necessity for DTs operating in real-time or near real-time.

```
Algorithm 2. Reversible Jump Markov Chain Monte Carlo with annealing temperature
  for L-System Optimization with Point Cloud Matching
Initialization:
current_L-system_state \leftarrow initial_L-system_state
best L-system state ← current L-system state
current\_fitness \leftarrow calculate\_fitness(current\_L\text{-system\_state, point\_cloud})
best_fitness \leftarrow current_fitness
temperature ← initial temperature
cooling_factor \leftarrow cooling_factor
Main Loon:
for i \leftarrow 1 to num iterations do
proposed\_L-system\_state \leftarrow perturb(current\_L-system\_state) \ // \ Randomly \ perturb \ the
  proposed\_fitness \leftarrow calculate\_fitness(proposed\_L\text{-system\_state}, point\_cloud)
  acceptance_ratio \leftarrow min(1, exp((proposed_fitness - current_fitness) / temperature))
  random_number \leftarrow random_uniform(0, 1)
  if random number < acceptance ratio then
     current_L-system_state \leftarrow proposed_L-system_state
     current\_fitness \leftarrow proposed\_fitness
     if\ current\_fitness > best\_fitness\ then
       best L-system state ← current L-system state
       best fitness ← current fitness
     end if
  end if
  temperature ← temperature * cooling_factor // Annealing schedule for temperature
end for
Output:
best_L-system_state
```

#### 5.4. FSPM

After obtaining measurements from the bio-sensors and external data variables, the plant model can utilize these measurements as variables (Table 4). It is notable that additional variables are required for comprehensive plant modelling. The purpose of including this demonstration is to provide an illustrative example. The selection of these four input variables is based on their fundamental role in influencing various physiological processes. These variables are crucial and widely applicable in modelling. The number of variables in plant models increases in complexity and granularity. Take, for instance, the CPlantbox model, which incorporates intricate molecular processes like rubisco activity

and water flow in photosynthesis. This model demands a multitude of variables and parameters, many of which are challenging to obtain (Zhou et al., 2020). Regarding parameters, their initial values are often derived from previous parametrization experiments. However, certain parameters that cannot be directly measured in plants are estimated using statistical methods, such as Bayesian statistics, to parametrize and calibrate FSPMs (Blanc et al., 2023). To provide an illustrative example of some parameters within this framework, parameters from a wellestablished crop model known as WOFOST (Van Diepen et al., 1989; Gilardelli et al., 2018) are presented in (Table 5). These parameters were chosen because of their relevance to plant architecture, which is one of the advantages of FSPM in comparison to PBM. After all the variables, parameters and the plant architecture (written in L-system and RGG derived from the point cloud) are integrated into the FSPM and provide the rendering needed to be able to visualize the DT, predictions for the next states of the model attributes are possible (Algorithm 3).

```
Algorithm 3. Functional structural plant modelling workflow
1:
Load data from sensors
2:
Input variables Input(x)
Initialize parameters
Initialize plants
Axiom ==> PlantarhcitectureinL - systemandRGG
  for i \in (growth days) do
  Update sun and sky (Input x)
  Run light model (Input x)
  Update parameters
  Apply rules
    if i:Intenrode and l:Leaf and n:Node <= end of growth then
  Update existing organs yo
  if i:Intenrode and l:Leaf and n:Node = end of growth then Formation of new organs
  end
Rules for substances transportation
Update output end
if i = (harvesting date) do
Store (Final output y)
```

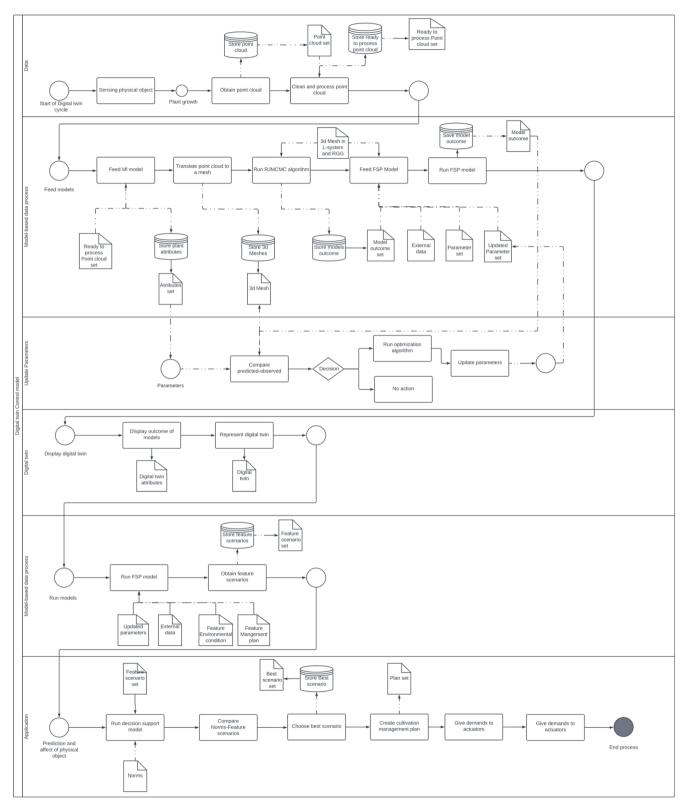


Fig. 7. DT control model architecture with FSPM integrated. The figure was constructed utilizing the Business Process Model and Notation (BPMN) 2.0 framework, as outlined by Chinosi & Trombetta (2012).

**Table 5**Variables of a plant model.

Variable	Description	Units
$\mathbf{x}_1$	Growing date	day
$\mathbf{x}_2$	Hourly global radiation	${ m MJ~m^{-2}~day^{-1}}$
$\mathbf{x}_3$	Hourly temperature	°C
$x_4$	Hourly carbon dioxide concentration (CO2)	μ mol/mol
у	Total dry weight	${ m g~m^{-2}}$
y <sub>0</sub>	Dry weights of different types of organs	${\rm g~m^{-2}}$

#### 5.5. Parameterization, calibration and model Update

After obtaining the output from 3D phenotyping and FSPM, the optimization of parameters for minimizing the difference between the observed values and the predicted values,  $J(\theta_i)$ , was determined using the mean square error and expressed as Eq. (1).

$$J(\theta) = \frac{1}{2} (y - \widehat{y})^T (y - \widehat{y}) \tag{1}$$

where y is the observed values coming from the 3d plant phenotyping and  $\hat{y}$  is the predicted values derived from the FSP model. The general algorithm of this process can be seen in (Algorithm 4). Similar work was investigated by Potapov et al, (2016) in which difference between the model estimation and the real tree coming from treeQSM was calculating the smallest distance and then the algorithm was adjusting the parameter values.

Algorithm 4. Estimation of parameters 1: Initialize parameters 
$$(\theta)$$
 load variables matrix  $(\begin{bmatrix} x_1 & \cdots & x_{1_t} \\ \vdots & \ddots & \vdots \\ x_n & \cdots & x_{n_t} \end{bmatrix})$  from sensor data for  $i \leq \text{end}$  of plant life cycle do: 2: Run FSPM Model  $f(x_1, x_2, x_3, x_4)$  Output: $\widehat{y}$  3: Perform 3d plant phenotyping. Output:  $y$  4: Calculate 
$$J(\theta_i) = \frac{1}{2}(y - \widehat{y})^T(y - \widehat{y})$$
 5: Update parameters  $(\theta_i)$ 

# 5.6. Model evaluation

After the completion of the plant's lifespan, the model's validation would involve assessing its performance based on the following criteria. The BIC is a widely used criterion in model selection that facilitates the evaluation and comparison of different models (Burnham & Anderson, 2002). It serves as a measure of the performance or goodness of fit of a model. The BIC value is calculated using the following equation, as proposed by Venables & Ripley (2002):

$$BIC = N*log\left(\frac{\sum_{l=1}^{N} (y_l - \widehat{y_l})^2}{N}\right) + p*log(N)$$
(2)

where N refers to the total number of available data points,  $y_l$  represents the observed values,  $\hat{y_l}$  represents the predicted values obtained from the model, and p denotes the number of parameters used in the model.

The RMSE is a commonly used criterion for assessing the accuracy of predictions by measuring the discrepancy between the predicted and observed values. It is represented by Equation (2), which quantifies the distance between these values.

$$RMSE = \sqrt{\frac{1}{N} \sum_{l=1}^{N} (y_l - \hat{y_l})^2}$$
 (3)

The modelling efficiency is a dimensionless metric utilized to assess the overall quality of fit between predicted and observed values. It quantifies the goodness of fit and is calculated using the formula proposed by Baey et al. (2013).

$$Efficiency = 1 - \frac{\sum_{l=1}^{N} (y_l - \widehat{y_l})^2}{\sum_{l=1}^{N} (y_l - \overline{y_l})^2}$$
(4)

where  $\overline{y_l}$  is the average of the observed values.

The Integrated FSPM-DT framework amalgamates methodologies to characterize and simulate plant behaviours and advance DTs in agriculture. Its initiation involves the aggregation of 3D plant model data, which subsequently undergoes refinement, segmentation, and the quantification of phenotypic attributes. This iterative progression spans diverse temporal instances, aligned with the plant's life cycle. The resultant phenotypic data imparts substantial visualizations, translating into L-system and RGG realm, thereby bridging the transition from raw data to discerning insights. These reconstructed plant architectures are then seamlessly incorporated into the FSPM. Consequently, the amalgamation of FSPM with the DT framework empowers dynamic analysis and prognostication of plant responses within intricate environments. FSPM serves as the pivotal substrate for comprehending growth, interactions, and behaviours, thereby fostering advancements in agricultural and ecological research. The integration of FSPM into the control model (Fig. 1) is demonstrated in the updated version (Fig. 7).

#### 6. Discussion

A domain analysis revealed the absence of 3D functional plant modelling in existing agricultural DT systems. Subsequently, a comprehensive study on 3D plant phenotyping was conducted, which involved examining various 3D sensing technologies and establishing a pipeline for plant reconstruction and derivation of plant traits (Fig. 5). Building upon these findings and recognizing their potential, a conceptual framework and pseudocode algorithms were proposed to integrate FSPM into agricultural DT systems. It is important to note that the proposed framework and algorithms specifically focus on the FSPM component and do not encompass the broader control aspects of the DT system (Fig. 1). The suggested approach revolves around leveraging 3D plant phenotyping techniques to enrich the FSPM with accurate representations of the physical object's plant architecture. This enables the creation of a DT that potentially faithfully captures the structural dynamics of the plant. Key plant traits, such as biomass and leaf area, are utilized as observed values, eliminating the need for manual measurements, and allowing for parameter estimation, calibration, and validation of the FSPM. This automated process of reconstructing the FSPM during the physical object's lifecycle paves the way for the development of a predictive DT. However, it is important to emphasize that integrating FSPM alone is insufficient to achieve a fully predictive DT. Other crucial aspects need to be considered and incorporated. This conceptual framework serves as an initial step towards integrating FSPM into DTs in agriculture. It provides a starting point for future research and development in this domain, highlighting the potential benefits of incorporating FSPM into DT systems. It is worth noting that DTs are highly complex systems, and their creation should be approached progressively by gradually adding and integrating various aspects to enhance their complexity (Pylianidis et al., 2022). While this proposed framework addresses the integration of FSPM, it is important to acknowledge that there are numerous other challenges and considerations that arise from both the DT perspective and the FSPM perspective. These challenges represent opportunities for further investigation and advancement in the field.

The proposed framework in this study assumes the use of relational growth grammars for 3D modelling. However, it should be noted that different approaches to FSPM may require alternative approaches. The choice of FSPM approach is typically determined by the researchers' institution and available literature, without specific reasons stated for selecting one approach over others. Nonetheless, Openalea (Pradal et al., 2008) offer a software solution that can integrate different FSPM software and approaches, enabling communication between models. In addition to FSPM, efforts have been made to connect FSPM with data models, resulting in improved performance compared to individual models. DT systems, which encompass cloud-based data storage, can support the fusion of data-driven models and FSPM to achieve more accurate results. Data-driven models, considered a fundamental approach in smart agriculture (Tantalaki et al., 2019), possess advantages, such as the ability to approximate nonlinear functions, strong predictive capabilities, and flexibility in adapting to multivariate system inputs. However, they lack the physical explanations and structural knowledge of the underlying system, treating internal processes as black-box entities (Fan et al., 2015). By combining the strengths of process-based plant models and data-driven models, the knowledgeand-data-driven modelling approach has emerged, overcoming the challenges of applying models in real-world agricultural settings (Kang & Wang, 2017). Fan et al. (2015) introduced the KDDM approach for plant growth simulation, which demonstrated the preservation of interpretable parameters, accurate prediction of dry weights of plant organs, compensation for uncertainties, and effective utilization of domain knowledge and ecological data. Overall, the KDDM approach greatly enhanced plant growth simulations. The KDDM approach has been successfully applied in various studies. For instance, Nascimento et al. (2020) implemented hybrid models that combine physicsinformed and data-driven kernels, with data-driven components used to bridge the gap between predictions and observations, as well as perform model parameter identification. Additionally, Xiao & Li (2022) demonstrated a novel approach employing model fusion to integrate non-destructive sensor data with a mechanistic model for kiwifruit softening during cool storage, allowing for a temporal description of flesh firmness retention.

# 6.1. The adding value of adding 3D functional plant modelling in DT for agriculture

The integration of 3D FSPM into DTs for agricultural purposes yields manifold benefits. In Table 6, a qualitative validation of the proposed framework is provided by means of reflection on how the framework could be realised in real world case study settings in comparison process-based models or data driven models; an approach adopted in earlier work by Tekinerdogan et al. (2020). The proposed framework demonstrates its potential utility in various real-world case study scenarios, particularly in enhancing yield prediction, disease prediction, and

**Table 6**Sample of parameters of the WOFOST model.

Parameter	Description	Units
TBASEM	Base temperature for emergence	°C
TSUMEM	Thermal sums to reach emergence	°C
TSUM1	Thermal sums from emergence to anthesis	°C-d
LAIEM	Leaf area index at emergence	$\mathrm{ha}~\mathrm{ha}^{-1}$
RGRLAI	Maximum relative increase in leaf area index	ha ha $^{-1}$ $^{\circ}$ C $^{-1}$ d $^{-1}$
PHYL	Phyllocron	°C day•leaf <sup>-1</sup>
CVL	Efficiency of conversion into leaves	kg ka – 1

intercropping strategies. In the case of DTs modelling greenhouse crops for yield prediction, FSPM-integrated DTs provide comprehensive insights into crop physiology, including detailed examinations of plant architecture, microclimate, and light absorption. This enables proactive identification and mitigation of potential issues, offering a more holistic understanding of crop yield dynamics compared to other DTs. Similarly, for disease prediction in greenhouse crops, FSPM-integrated DTs outperform others by providing insights into affected plant parts, offering detailed understandings of disease causation, and exploring the efficacy of preventive measures such as pruning techniques or crop formation. This allows for more effective disease management strategies. In the scenario of intercropping, FSPM-integrated DTs excel in providing abundant insights crucial for understanding the interactive dynamics between different crops. By capturing spatial and temporal factors vital for intercropping dynamics, FSPM-integrated DTs facilitate the creation of scenarios for optimizing the mixture ratio of intercropped crops, thereby enhancing decision-making in intercropping practices. The absence of 3D functional plant modelling within DTs would hinder interaction with the architectural characteristics of plants, thereby complicating subsequent steps, such as the application of scenarios generated by the model. Moreover, essential practices like pruning regimes, which significantly contribute to yield and fruit quality in crops such as tomato, peaches, and apples (Ara et al., 2007; Kumar et al., 2010; Hampson et al., 2002), would be impracticable. This limitation extends to disease prevention strategies as well. Overall, the incorporation of FSPMs into DTs significantly enhances their capabilities in understanding and managing agricultural systems, offering more nuanced insights, and facilitating more informed decision-making compared to other DT approaches. Table 7

Moreover FSPM-integrated DTs can assist to create dynamic DTs in virtual reality, Spyrou et al. (2023) showcased a DT for cannabis cultivation; however, the static nature of plant representation in the virtual environment precluded the incorporation of actual growth dynamics inherent in mechanistic models. Integration of FSPM within the DT framework can address this limitation, facilitating immersive experiences wherein plant growth and physiology are dynamically simulated. Extending beyond virtual environments, Extended Reality (XR) technologies hold transformative potential for agricultural domains (Anastasiou et al., 2023). XR technologies offer avenues for enhanced decision-making, training, and system development across agricultural sectors. The integration of 3D plant functional modelling into DTs is paramount, as it enables seamless interaction between crop models and plant architecture, thereby facilitating scenario-based applications such as pruning regimes and disease prevention strategies. A study conducted by Majeed et al. (2020) demonstrated the use of deep neural networks for segmenting apple branches and trunks. However, a limitation arises from the absence of radius information of the branches, crucial for pruning decisions. Integration with DTs can bridge this gap, enabling the incorporation of radius data into neural network models. Furthermore this integration, coupled with techniques like L-system transformation and hybrid AI-procedural models, fosters synergies between architectural details and pruning algorithms. Consequently, autonomous DTs can leverage this amalgamation to provide comprehensive instructions to robots for precise pruning operations, benefiting from enhanced branch information and scenario assessment facilitated by FSPMintegrated DTs.

The paramount significance of high-quality data in facilitating the efficacious utilization of AI remains integral to ensuring food security (Tsiligiridis & Ainali, 2018). Despite the increasing availability of data and advancements in AI methodologies, a gap persists in leveraging AI tools effectively within the plant science community (Williamson et al., 2021). DTs offer a conduit for generating and disseminating high-quality data, thereby facilitating advancements in plant phenotyping and training of deep neural networks. This is exemplified by the utilization of time-series data of plant architectures for training ML models to capture complex relationships. Additionally, in the realm of food security, efforts

**Table 7**Advantages of DT with integrated FSPMs in comparison process-based models (PBM) or data driven models.

	Dt with no model	Dt data driven	Dt with PBM	Dt with FSPM
DT of a crop in a greenhouse for yield prediction	Illustration of greenhouse crop cultivation minus functional attributes and crop physiology insights. Devoid of yield projections and disease predictions.	Depiction of greenhouse crop without functionality or insights. Nonetheless, future predictions and scenarios may be presented without elucidation of underlying reasons.	Depiction of greenhouse crops with limited insights and functionality confined to a one-dimensional aspect. Additionally, prospective scenarios and predictions can be evaluated to identify potential measures for preventing solutions.	Representation of greenhouse crop with insights and functionality in three dimensions. Additionally, potential scenarios and predictions can be evaluated to proactively identify and address issues. Thorough insights explore the influence of plant architecture and formation on crop yield, including a detailed examination of microclimate and light absorption.
DT of a crop in a greenhouse for disease prediction	Monitoring crop without delving into disease progression or causative factors.	Monitoring crop, incorporating probabilities of disease occurrence. However, lacking insights into preventive strategies.	Monitoring crop while providing insights into diseased plants, expressed as a ratio or count. Offering insights on potential infections and advising on management measures to avoid.	Monitoring crops with insights into affected plant parts. Providing insights on potential infections, recommending avoidance of specific management measures, and offering a more detailed understanding of disease causation. Additionally, exploring the efficacy of preventive measures such as pruning techniques, planting distances, or crop formation.
DT of intercropping	Representation and monitor of the intercropping.	Representation and monitoring of intercropping with minimal insights, as data-driven models face challenges in achieving high accuracy due to numerous nonlinear factors.	Representation and monitoring of intercropping with a more substantial number of insights derived from datadriven models. However, the intricate nature of intercropping, influenced by various spatial and temporal factors, remains a challenge for precise modelling with PBMs.	Representation and monitoring of intercropping with abundant insights facilitated by FSPM. FSPMs allow capturing spatial and temporal factors crucial for intercropping dynamics. Creating scenarios for the mixture ratio of intercropped crops, these insights aid in understanding the interactive dynamics between different crops.

in breeding aim to integrate breeding practices with crop modelling to elucidate Genotype x Environment x Management (GxExM) interactions, thus enhancing predictive capabilities and annual yield gains (Cooper et al., 2021). Furthermore, it is imperative to highlight the significance of end-users, predominantly farmers, who stand to benefit from interacting with procedural modelling. The quantitative nature of outputs derived from process-based modelling often proves challenging for farmers to comprehend and utilize effectively. Conversely, FSPMs provide visual representations, making DTs with integrated FSPMs more user-friendly and accessible to end-users. By providing optical outcomes of experimental scenarios, such as assessing pruning schemes and their subsequent impacts on plant growth, DTs equipped with FSPMs enable farmers to comprehend and engage with the results more effectively compared to conventional process models, which typically present results in abstract graphical formats. Furthermore, this facilitates practical training in agronomic practices such as pruning, contributing to enhanced usability and adoption of agricultural DTs among end-users. Ultimately, the integration of FSPMs within DTs holds promise for advancing agricultural DT technology, fostering greater accuracy and usability for end-users.

#### 6.2. Challenges in the integration of 3D modelling in DTs

#### 6.2.1. Training of ML algorithms

The process regarding the ML training was not discussed in this paper. Many research studies face the challenge of limited data availability for training ML algorithms (Masuda, 2021; Chebrolu et al., 2021). However, an alternative source of training data can be derived from plant images generated by FSP models. Chaudhury et al. (2020) have introduced a generalized approach for generating labelled 3D point

cloud data from procedural plant models.

# 6.2.2. Scaled up

The proposed framework in this article focused on representing individual plants within a physical object, but further research is needed to parametrize the FSPM at different scales. Most existing research in the literature primarily focuses on parametrization at the plant level, while parametrization at the field level is less explored. It is essential to consider the functional differences between plants at the individual and field levels. However, deriving 3D parameters from the single plant scale to the field scale poses significant challenges (Paulus, 2019). Furthermore, accurately representing each plant's location within the growing environment, such as a greenhouse or field, is crucial for the model to incorporate plant-to-plant interactions. Therefore, the digital object must include information about its position, such as GPS coordinates, to accurately place the plant in the virtual experiment. Additionally, if the DT aims to consider other stakeholders involved in decision support systems, as well as market connections, the agricultural domain presents unique challenges. Agriculture is a complex system involving multiple stakeholders. Wang et al. (2020) proposed a blockchain-enabled Integrated Horticulture Supply Chain (IHSC) and introduced a simulationbased DT to enhance transparency, safety, security, and efficiency in the supply chain. This platform enables process risk analysis and provides decision-making guidance. Empirical results demonstrate the promising performance of the proposed platform.

#### 6.2.3. Communication

Effective communication between different components of the DT is a crucial aspect. While extensive work has been done on the Internet of Things domain, where various communication protocols have been

developed for DT applications (Popović et al., 2017; Dholu & Ghodinde, 2018), challenges still remain in connecting and synchronizing data from proposed algorithms and coordinating the different compartments of the DTs' control model (Fig. 3). The diverse range of applications in digital phenotyping necessitates the use of multiple frameworks within the same cluster, as it is not feasible to develop all applications within a single framework. Apache Mesos provides an optimal solution by enabling fine-grained resource utilization within a cluster without the drawbacks associated with multiple Virtual Machines or cluster partitioning. Debauche et al. (2017) proposed a novel approach that combines logic synthesis and cloud architecture in a lambda cloud framework, specifically tailored to meet the requirements of digital phenotyping. This approach enables real-time storage and processing of the substantial amount of data involved. A case study conducted in a controlled environment system, such as a growth chamber, focused on growing basil plants, showcasing the practical implementation of this approach.

#### 6.2.4. Environment

FSPMs not only simulate the plants themselves but also incorporate the modelling of the surrounding environment, including the simulation of microclimates within different parts of the plant. This comprehensive approach enhances the realism of the virtual environment and improves the accuracy of the FSPM, thereby enhancing the fidelity of the DT. While the initial proposed conceptual framework overlooked the environment, numerous researchers have since dedicated their efforts to accurately simulating and incorporating the environmental factors. A numerical simulation model was developed to accurately predict greenhouse temperature and radiation distributions for the purpose of greenhouse microclimate control (Ma et al., 2019). The model was successfully applied to simulate temperature and radiation profiles over time and space within the greenhouse at Purdue University. By leveraging the simulation results, this study demonstrated how the optimization of conveyor system movement could be informed quantitatively to minimize greenhouse microclimate variations. Light modelling.

# 6.2.5. Twinning and twinning rate

The determination of twinning and twinning rate within a DT is a crucial aspect that currently lacks comprehensive research. In the study in this article, we propose adopting a flexible time step depending on the objectives of the DT usage. For applications that primarily focus on capturing fast-changing biological states and assessing plant conditions, a longer time step, such as daily, may be deemed insufficient for capturing meaningful differences and retaining crucial states. Discretizing time is a common practice in modelling and simulation, particularly since many processes cannot be analytically integrated over time and, therefore, require discretization. The choice of time step should be carefully adjusted and considered for future investigations. In simulation models of plant development, physiological processes occurring within plants are often described using Ordinary Differential Equations. In this context, the incorporation of artificial intelligence AI techniques can be advantageous. By integrating Ordinary Differential Equations with AI, the proposed approach allows for real-time controls (Nascimento et al., 2020). It is important to note that a main limitation of the resulting model is the assumption of a constant system, which may be unrealistic in practical settings. Furthermore, the current state of the model only considers time-independent covariates, indicating a need for further refinement and consideration of time-varying factors.

#### 6.2.6. Metrology

Although the proposed conceptual framework did not initially consider metrology, it is an essential and highly technical aspect that must be addressed in order to adapt to the specific circumstances of the physical object's environment. The incorporation of metrology is challenging but crucial. Farooq et al. (2020) conducted a comprehensive study on the application of IoT technology in agriculture, which may provide valuable insights in this regard.

## 6.2.7. Abstraction level of FSPM

The paper under discussion does not provide an explicit discussion on the level of granularity of the FSPMs. However, it is important to note that the choice of granularity depends on the objectives of the DT. Moreover, as the complexity of the model increases, so does the computational time required for the entire DT system. For instance, in the case of CPlantBox, the inclusion of a higher number of modules results in an increased number of parameters and intermediary outputs, which subsequently leads to longer computational time (Giraud et al., 2023). Furthermore, certain variables and parameters cannot be measured experimentally, such as the separation of respiration between maintenance and growth, making their evaluation more challenging. It is worth mentioning that while some FSPMs are stochastic, for the purposes of DT implementation, mechanistic models are recommended as they provide a rationale behind predictions that are contingent upon the environmental conditions of the digital environment. On the other hand, stochastic models are parameterized based on experimental conditions, limiting their applicability to specific experimental setups. Furthermore, the inclusion of realistic leaflet representation in FSPMs has a significant impact on dynamic models but is less influential in static models (Vermeiren et al., 2020). Lastly, it is noteworthy that only a few FSPMs consider both the root and upper plant systems, as well as their interconnectedness. The selection of FSP models depends on the objectives of the DT, allowing for the choice between models that solely consider the upper plant or those that incorporate the root system as well. An example of a comprehensive FSPM that accounts for both shoot and root growth, as well as their interactions, is the RoCoCau structural whole-plant growth model, which employs the architectural unit concept and incorporates specific functions based on experimental measurements in the shoot and root compartments (Masson et al., 2022).

#### 6.2.8. Decision making with AI and FSPM

The article does not address the connection between the predictions and outcomes of FSPMs and their integration with decision support systems. However, there have been efforts to combine FSPM outcomes with decision support systems for improved decision-making in various domains. For instance, Utama et al. (2022) employed a plant dataset, the GroIMP-FSPM platform, and fuzzy logic to develop a model that could assist researchers in making informed decisions based on the Break-Even Point evaluation. By integrating FSPM predictions into the decision support system, the model provided valuable insights to researchers, aiding them in making more effective decisions. Moreover, the integration of virtual plant models with other constructed models, such as Dynamic Simulation Models, has been explored to simulate investment strategies in green-leaf vegetable production. Utama & Wibowo (2021) proposed a model that recommended the optimal number of plants to be cultivated in a hydroponic system in order to maximize profitability. This integration of the FSPM with the Dynamic Simulation Models enabled investors to make informed decisions regarding their

investment in green-leaf vegetable production. Furthermore, Jabar & Utama (2021) successfully utilized a combination of the Plant Construction Model and Dynamic Simulation Models methods in a virtual hydroponic green amaranth plant model. This research facilitated decision-making for farmers engaged in hydroponic green amaranth plant cultivation, enabling them to make strategic decisions based on the outcomes of the virtual plant model. These studies highlight the potential of integrating FSPM predictions with decision support systems, offering valuable guidance and support for decision-makers in various agricultural contexts.

## 6.2.9. Virtual to physical

The control model depicted in this article demonstrates the communication and influence of the DT on physical objects through the utilization of actuators. However, an extensive review of the literature revealed that most existing studies primarily focus on unidirectional data flow, specifically from the physical realm to the DT. The investigation into the data flow from the DT to the physical twin, occurring after the execution of the DT simulation and involving the use of actuators, requires further in-depth research (Segovia & Garcia-Alfaro, 2022). Furthermore, the current body of literature lacks research on how the DT, through the implementation of actuators, impacts the physical twin. Furthermore, the discussion on the integration of enabling technologies was notably absent. For a comprehensive analysis of the enabling technologies utilized in existing DT implementations, one can refer to a systematic review conducted by Fuller et al. (2020).

#### 6.2.10. Parametrization, Validation, calibration.

The parametrization and validation of the DT framework proposed rely on observed values obtained through 3D phenotyping. While 3D phenotyping is increasingly approaching reality (Paulus, 2019), it is not considered the ground truth. Therefore, it is crucial for 3D phenotyping to achieve high accuracy and closely resemble reality. This is important because a DT should be able to parametrize and validate its models using non-destructive methods, as the actual crops are intended for sale and cannot be treated as experimental samples. Furthermore, it is important to note that the incorporation of the 3D plant architecture derived from 3D plant phenotyping into the FSPM introduces the possibility of bias, as the model may exhibit similar behaviour. Therefore, caution must be exercised in this regard. Additionally, the validation process can include evaluating different previously saved stages in the history of predictions for DTs. This allows for overtime calibration and parametrization, although the discussion of this aspect is more complex, as it involves processing and assessing historical data alongside the final yield.

# 7. Conclusion

In this study, the Integrated FSPM-DT framework combines methodologies to characterize and simulate plant behaviours. Starting with 3D plant data, it refines, segments, and quantifies phenotypic traits iteratively across the plant's life cycle. This results in visualizations translated into L-system and RGG representations, seamlessly integrated into the FSPM. This fusion enables dynamic analysis and prediction of plant responses in complex environments, advancing agricultural and ecological research. The proposed framework offers dual benefits. Firstly, it replaces traditional plant sampling for model optimization and

calibration with data sourced from 3D plant phenotyping. This shift not only streamlines the process but also enables DTs to validate and calibrate FSPMs using non-destructive methods. Secondly, this approach carries the potential to enhance prediction accuracy beyond that of conventional FSPMs, potentially leading to even more accurate predictions. Ultimately, providing an interactive environment to end-users can significantly enhance adoption rates.

However, this is a conceptual framework explaining how an FSPM approach can be integrated with DTs. To that end, to create a DT in agriculture many different domains need to collaborate and work together, as all the parts of the DT need to be connected and be compatible. We suggest that, in future work, a unified platform must be created that can be user-centric. It appears that FSPMs can be benefited from DTs and DTs in agriculture can further evolve to incorporate prediction and automation services more widely. Also, FSPMs can be used in the training of the ML algorithms in a DT. Plant models are valuable for predicting and optimizing plant growth while reducing costs and resource usage. Despite their benefits, farmers often don't use them due to complex software, unfamiliar plant terminology, and challenging graph interpretation. DTs can offer a solution by providing user-friendly interfaces and using non-scientific language for easy interaction with plant models. To that end, DTs and FSPMs can benefit at the same time each other. Future research should focus on implementing and modifying existing codes to meet the specific needs of a case study within the context of DTs. This implementation should be guided by the proposed conceptual framework, aiming to assess computational time and ensure data compatibility across different output sources. By customizing the codes and integrating them into the framework, researchers can evaluate computational efficiency and harmonize data outputs effectively. Consideration should be given to factors such as software compatibility, code dependencies, and case study requirements to ensure successful implementation. This research will contribute to advancing 3D DT applications and improving their reliability and effectiveness.

#### CRediT authorship contribution statement

Christos Mitsanis: Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Conceptualization. William Hurst: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. Bedir Tekinerdogan:

#### **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.

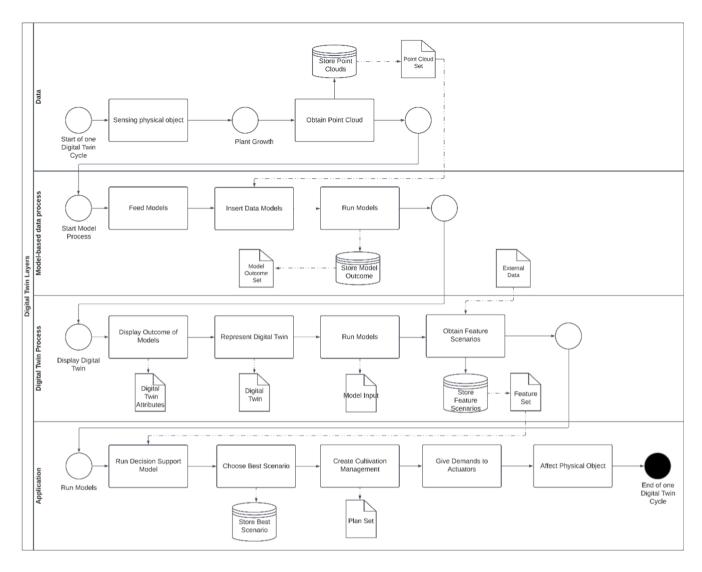
#### Data availability

Data will be made available on request.

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#### **Appendix**



Appendix A. Conceptual model for Digital Twins, based on Verdouw et al. (2015). The figure was constructed utilizing the Business Process Model and Notation (BPMN) 2.0 framework, as outlined by Chinosi & Trombetta (2012).

Appendix B. Key concepts related to DTs (adapted from Jones et al., 2020).

Term	Explanation	
Physical twin	The physical object that exists in the real world	
Virtual twin	The virtual object that exists in the virtual world	
Physical Environment	The environment in which the physical object exists	
Virtual Environment	The environment in which the virtual object exists	
State	The recorded values for all parameters associated with the physical or virtual entity/twin and its surrounding environment.	
Metrology	The process of capturing the state of the physical/virtual entity	
Realization	The process of altering the state of the physical/virtual entity.	
Twinning	The process of aligning the states of the physical and virtual entity.	
Twinning Rate	The frequency at which twinning takes place.	
Physical-to-Virtual communication	The data connections and processes involved in capturing the state of the physical twin/environment and replicating that state in the virtual twin/environment.	
Virtual-to-Physical communication	The data connections and processes involved in capturing the state of the virtual twin/environment and replicating that state in the physical twin/environment.	

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