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Forest digital twin: A new tool for forest management practices based on Spatio-Temporal Data, 3D simulation Engine, and intelligent interactive environment

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ABSTRACT

Existing forest digitization studies focus on one-way forest management practice visualization simulation, lacking decision-making feedback and virtual-real interaction synchronization. This paper presents the vision of the forest digital twin paradigm. We construct a forest digital twin to explore a new digital carrier of forest resources using remote sensing data, forest inventory data, the Cesium Digital Earth Engine, forest planning theory and parametric 3D modeling technology. The two-way interaction and thinning experiments showed that the forest digital twin could provide a novel pattern for in-depth analysis of forest spatial structure, individual tree dynamic growth and human-digital twin interaction effects. The successful recognition rate in matching the forest structure seen on real forest structure images with the forest digital scene was 91.3%, indicating that the forest digital twin can characterize the real forest structure significantly. The prediction accuracy of the multi-grade growth model integrating the Bayesian method for DBH, H was more than 90.4%. In addition, ASS-FDT interaction is superior to the assessors (ASS) and forest digital twin (FDT) for stand spatial structure overall optimization. The multi-dimensional stand spatial structure index (F-index) increased by 22.82%. The constructed forest digital twin model shows superior performance in optimizing the stand growth model and enhancing the overall stand spatial structure under the decision-making feedback and real-time interaction strategies. The automatic operation pattern provides a user-friendly forest management practice solution.

1. Introduction

A digital twin is a computer-generated equivalent of the actual physical world that can simulate physical objects, physical states, and processes. It is widely used in aerospace, machinery manufacturing, and robot fields. However, there are still no common approaches, standards, definitions, or guidelines (Tao et al., 2018; Duan et al., 2021). With the explosion of visualization software, data mining, multi-source data fusion, and deep learning technologies, digital twins of the physical entities enable engineers, doctors, data scientists, and IT experts to predict the potential state and development of the actual objects, which will help them to take corresponding optimization measures to enhance team effectiveness. Recently, the concept of digital twins has been dramatically expanded, and digital twins of cities, buildings, medical care, and ports have been proposed (Peng et al., 2020; Fan et al., 2021). Miller et al. (2021) showed that Human Digital Twin (HDT) is an effective and practical way to achieve full life cycle health and fitness management. However, few studies have reported the application of digital twin technology in geographic information, forest ecology, and sustainable forest management.

Recently, 2D and 3D visualization software have developed extremely rapidly, but advanced VR and XR technologies and CAVE2 visualization systems are still rarely applied in forest management practice simulations (Fabrika et al., 2018). For example, thinning, tending, replanting and pruning are practical activities in the forest management practices that play a vital role in many aspects, such as maintaining the forest ecosystem stability, reducing greenhouse gas emissions, resisting climate change, windproof and sand fixation, and

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Table 1
The merits of VR, XR, CAVE2 and digital twins.

Technology	VR	XR	CAVE2	Digital twin
Define	Creating a completely virtual environment, interacting with users through head-mounted devices	Including many virtual interaction technologies, AR and MR (Mixed Reality)	An immersive, 3D environment that projects images onto the entire room using a large-scale stereoscopic projection system	Seamlessly connecting physical-world entities with digital models to achieve real-time monitoring, prediction, and optimization
Application	Games, entertainment, simulation	Games, entertainment, training, industrial design, health care	Games, entertainment, training, industrial design, health care and forestry	Aviation, industry, city, energy, urban planning, health care
Advantage	A fully immersive experience, highly customizable, and entertaining	Can combine virtual and real worlds to improve efficiency and experience	Large-scale, realistic 3D environments that support team collaboration and interaction.	Two-way interaction, virtual-real synchronization, and Decision-making feedback. Improve efficiency, reduce costs, optimize resource allocation, and contribute to forest sustainable development
Limitation	Lack of interaction between the physical world and the virtual environment	XR is still in the development stage. Integrating XR with existing infrastructure can be complex	It requires specialized hardware and facilities. It is difficult to popularize to the mass market	Relying on the reliability and stability of IoT and sensor data

water-holding (Garcí a-Nieto et al., 2013; Chen et al., 2022). Some previous studies have developed a large variety of specialized tools for forest visualization, such as BWINPro software, SVS, Smart Forest, SILVA, BALANCE and Virtual Forester (Stoltman et al., 2004; Fabrika et al., 2018). However, these products focus on the construction of tree-, stand-, and landscape-level models, terrain, and environmental factors, lacking the quantization and visual feedback of the stand disturbance. They typically pay less attention to the performance and development potential of visual interaction thinning simulation. In addition, the effect of forest management practices on the stand structure or ecosystem would take decades to be seen. Traditional visualization approaches lack the immediate and real-time feedback that would provide users with stand structure and quality. Currently, with the improvement of computer graphics and image processing capability, it is possible to accurately and comprehensively present forest 3D information and forest development processes by using 3D engine and intelligent interactive software (Fujisaki et al., 2007; Hochschild et al., 2020). The coupling of a 3D engine and intelligent interactive software (IIE) will provide more possibilities for forest digital twin implementation in the next decade (Yu et al., 2022). Compared to virtual reality (VR), extended reality (XR), and CAVE2, digital twins exhibit tremendous potential in forest management practices (Table 1).

Tree growth is a crucial component in the construction of a digital twin of a forest. Tree growth is influenced by various interacting biotic and abiotic factors, including genetic traits, tree size, climate, competition, and forest management practices. Forest growth models typically describe the relationship between stand growth and variables such as stand conditions, stand-level covariates, and site conditions using mathematical functions. Individual tree models can be further divided into distance-independent and distance-dependent models. Current models are primarily established to predict tree growth by considering tree-site conditions, climatic factors, and physiological processes, thus capturing the interaction between tree growth and environmental factors. However, these models lack consideration of the interaction and feedback between target tree and neighboring trees. Currently, tree grading growth models incorporating stand structure parameters have gained widespread attention due to their consideration of the relationship between target trees and neighboring trees.

Forest inventory data, thematic forest maps, silvicultural plans, harvesting practices, and structure indices are key visualization elements of forest management practices (Zambelli et al., 2012; Soubry et al., 2021). However, these visualization elements only provide a general overview of forest resource information or characterize stand one-dimensional spatial structure features within a certain range of time and space (Fujisaki et al., 2007; Vagizov et al., 2021). Therefore, detailed descriptions and portrayals of stand spatial features or individual tree attributes are lacking, and decision-making measures lag behind forest development succession. At present, traditional forest spatial structure visualization suffers from three main challenges:

1. How to accurately display the tree species diversity, underlying surfaces, individual tree attributes, and the number of trees in natural forests or natural secondary forests with complex spatial structures—this is the basis of forest management practices (Stoltman et al., 2004; Nafees et al., 2019).
2. How to determine the distribution area and spatial arrangement of individual trees and the distribution of environmental elements such as trees, roads, and rivers throughout the forest landscape is essential for spatial planning of forest landscapes and evaluation of the degree of forest fragmentation (Falcão et al., 2006; Spathelf et al., 2018).
3. How to provide real-time decision-making feedback, virtual-real synchronization and 3D visualization of the process of harvesting practices can help forest managers determine which harvesting or nurturing practices to optimize stand structure and effectively improve stand quality in different stands (Karjalainen et al., 2002; Radhakrishnan et al., 2020).

Currently, growth models primarily rely on independent environmental factors or structural parameters as constraints to simulate tree morphological structure growth, lacking consideration of the impact of the growth environment and stand spatial structure differences. Existing research focuses on one-way visualization simulation of forest management practices, such as individual tree growth visualization, tree competition visualization, light radiation distribution of individual tree crown simulation, and one-way thinning simulation based on stand spatial structure indices, lacking decision-making feedback and virtual-real interaction synchronization. The forest digital twin remains poorly studied. Therefore, this paper aims to develop a new tool for forest management practices and explore the potential application possibilities. The following studies were conducted: (1) Grade the spatial structure of Chinese fir trees. (2) Develop a graded growth model by integrating the Bayesian method and parameter optimization algorithms. (3) Develop a forest digital twin using a 3D engine, spatiotemporal data, and IIE. (4) Construct the dynamic stand growth model to enhance the simulation effect of the forest digital twin. (5) Explore the impact of users and forest digital interaction on forest management practices.

2. Materials and methods

2.1. Study area and data collection

The first study area is located in Huangfengqiao Forest Farm (113°04′-113°43′E, 26°43′-27°06′N) in eastern Youxian County, Hunan Province. The altitude ranges from 115 m to 1270 m above sea level. It belongs to the humid subtropical monsoon climate. The average annual

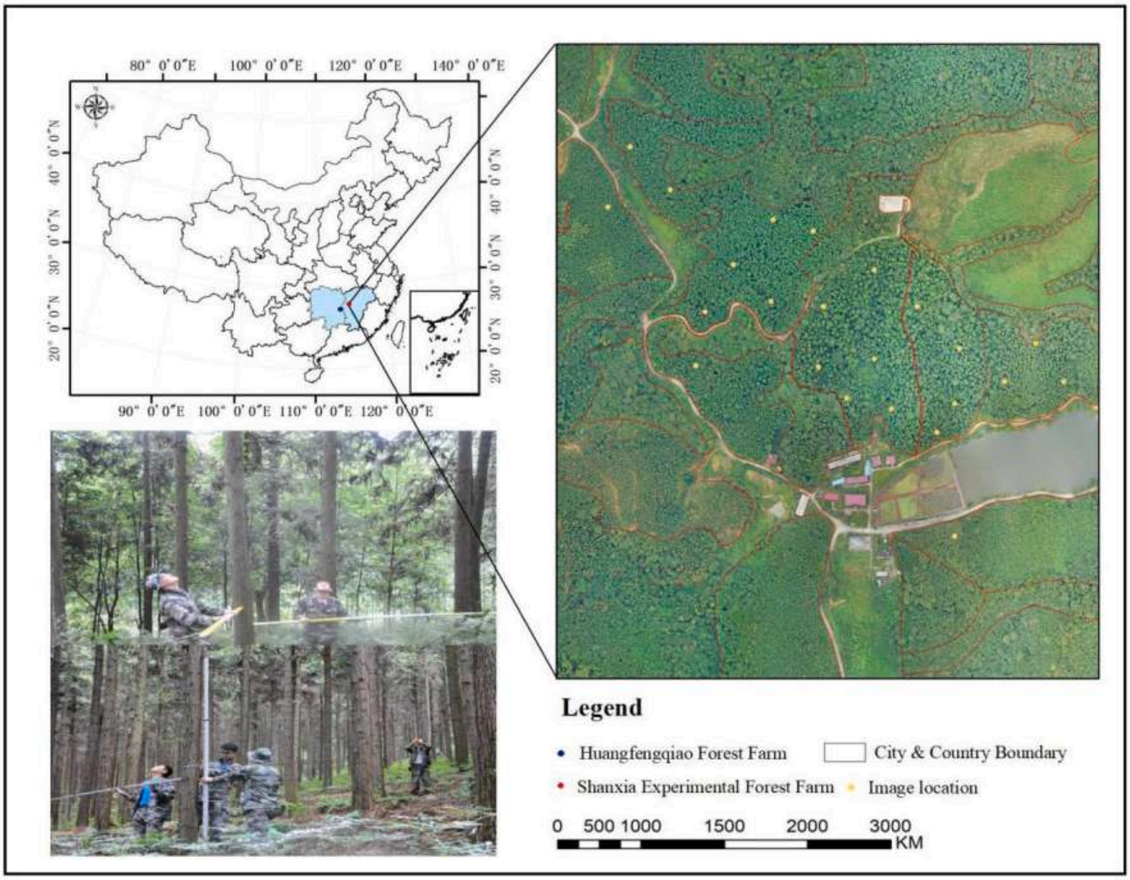

Fig. 1. Location of Huangfengqiao Forest Farm and Shanxia Experimental Forest Farm in south China.

Table 2
Plot information in the study area.

Plot	Area/ hm^2	Age	Number	DBH/ cm	H/m	CW/ m	UBH/ m
HN1	0.36	17–22	533	16.2 (7.1, 28.6)	10.6 (4.3, 18.0)	2.7 (0.6, 3.8)	5.0 (1.7, 9.3)
HN2	0.40	23–28	362	14.2 (5.9, 21.2)	9.5 (5.3, 13.5)	2.7 (0.8, 4.0)	4.3 (1.9, 7.5)
HN3	0.25	11–16	309	11.6 (3.2, 22.4)	8.4 (3.2, 13.7)	2.2 (0.3, 3.8)	4.4 (1.3, 8.0)
HN4	0.48	10–15	955	20.0 (10.5, 29.8)	12.8 (6.7, 16.8)	3.0 (1.6, 4.5)	6.6 (2.6, 9.2)
HN5	0.36	16–21	230	16.5 (6.2, 23.2)	11.0 (5.6, 13.8)	3.4 (1.8, 5.6)	6.3 (1.8, 9.5)
HN6	0.16	13–18	120	22.6 (13.3, 33.4)	15.4 (8.4, 20.2)	2.9 (1.3, 4.2)	8.2 (1.8, 12.2)
JX1	0.36	18–27	427	19.8 (6.3, 37.7)	12.6 (5.1, 19.0)	3.2 (0.5, 4.3)	7.7 (1.6, 14.5)
JX2	0.45	13–24	739	13.3 (5.5, 26.2)	9.3 (4.2, 13.0)	2.4 (0.3, 3.8)	6.3 (1.3, 10.3)

temperature is 17.8 ℃. The mean annual rainfall is 1410.8 mm. In addition, to check system fluency and large-scale scene rendering effects, we also extracted the individual tree attribute information and reconstructed trees to test system capacity from the UAV-Lidar point cloud and UAV image of the Shanxia Experimental Forest Farm (27°40′-27°45′ N, 114°35′-114°40′ E), which is located in the southwest of Fenyi County, Xinyu City, Jiangxi Province, China (Fig. 1). Our team and forest farm staff conducted ten field surveys in Chinese fir plantations at Huangfengqiao Forest Farm and Shanxia Experimental Forest Farm (2012–2017, 2019–2023), with a nearly annual survey frequency. Individual tree coordinates, tree age, diameter at breast height (DBH), tree height (H), crown width (CW), and under living branch height (UBH) were recorded using RTK, GPS, and tape measures. The distribution information of DBH, H, CW, and UBH for the HN1-HN6 (aspect: south slope, slope: 5-10°, elevation: 270–320 m) and JX1-JX2 plots (aspect: east-south slope, slope: 15-35°, elevation: 90–250 m) is shown in Table 2 and Fig. 2.

In our study, we created a 3D tree model with a more realistic texture and verified the accuracy and reliability of the forest digital twin. We also collected texture information from the study area several times. Texture photos of 1366 were mainly recorded by digital cameras, including the texture and morphological characteristics of bark, branches, and leaves, as well as the texture characteristics of buildings, roads, and water surfaces in the study area.

2.2. Neighborhood indices

To accurately demonstrate the relationship of neighboring trees and characterize variations in stand structure, we compiled the widely used and representative stand spatial structure indices: uniform angle, DBH dominance, openness, spatial density index, the Hegyi competition index, and the forest layer index (Pommerening, 2002; Hui et al., 1999; Aguirre et al., 2003; Hegyi, 1974). They reflect the spatial distribution pattern of individual trees, the spatial advantage degree, openness, the degree of crowding, the competitiveness of individual trees, and the vertical spatial distribution pattern of stand (Table 3).

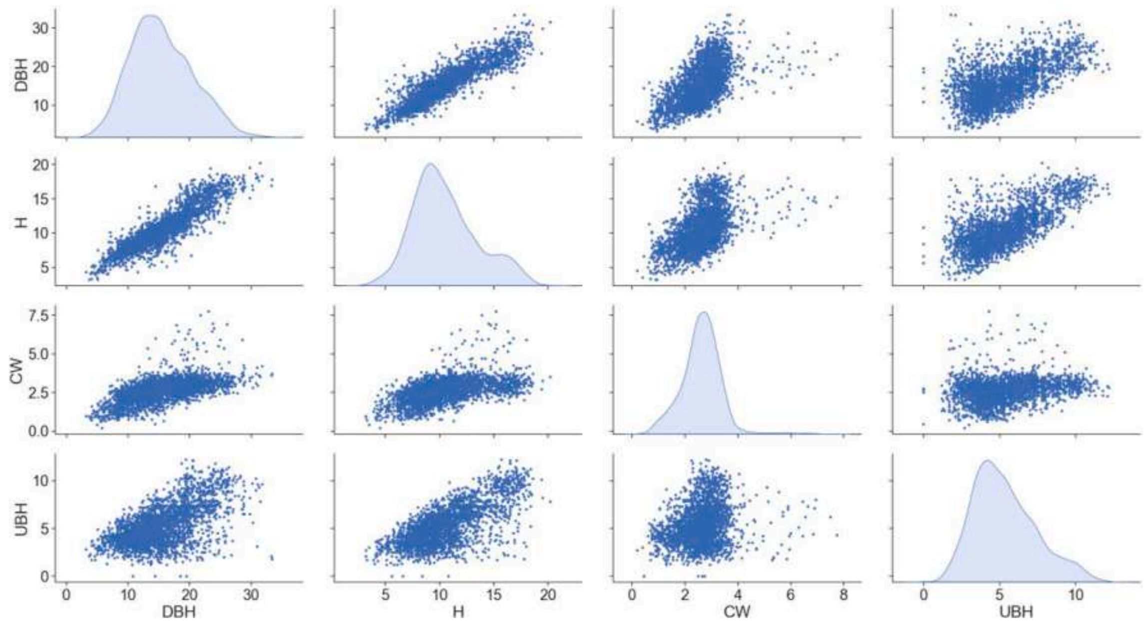

Fig. 2. Tree DBH-H-CW-UBH relationships of Chinese fir.

Harvesting is one of the essential measures in forest management. Therefore, when formulating harvesting strategies, stand spatial structure multi-objective optimization is a dynamic optimization problem. Each objective is independent, but they also mutually influence each other. To maintain the overall stand health and stability, tree species diversity, inter- and intraspecific competition, and tree distribution should be taken into consideration. Regardless of the chosen forest management approach, it is essential to comprehensively assess the overall stand spatial structure rather than relying on single structural indices, considering that the horizontal and vertical spatial distribution patterns of trees and tree competition are the main influencing factors of forest spatial structure. Therefore, in our study, we selected the Uniform angle index, DBH Dominance, Openness, Spatial density index, the Hegyi competition index, and Forest layer index as constraints of the evaluation function, constructing a multi-dimensional stand spatial structure index (F) based on utility theory and stand structure indices to describing the stand overall spatial structure (Pukkala et al., 2003).

$$F_i = \frac{\frac{1+S_i}{\sigma_{S_i}} \cdot \frac{1+OP_i}{\sigma_{OP_i}}}{[1+CI_i] \cdot \sigma_{CI_i} \cdot [1+W_i] \cdot \sigma_{W_i} \cdot [1+U_i] \cdot \sigma_{U_i} \cdot [1+D_i] \cdot \sigma_{D_i}} \tag{1}$$

$$F = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{2}$$

where W_i, U_i, OP_i, D_i, CI_i, and S_i are the uniform angle, DBH dominance, openness, spatial density index, the Hegyi competition index, and forest layer index of the target tree i, respectively; N is the total number of trees in the stand; n is the number of the neighbors of the target tree i; σ_{W_i}, σ_{U_i}, σ_{OP_i}, σ_{D_i}, σ_{CI_i} and σ_{S_i} are the standard deviation of the uniform angle, DBH dominance, openness, spatial density index, the Hegyi competition index, and forest layer index of the target tree i, respectively; F represents the overall level of stand spatial structure.

Accurately simulating the morphological-structure variation of individual trees due to external environmental disturbance is a prerequisite for constructing forest digital twins. Many forestry researchers have proposed a multi-grade morphological structure index to simulate the impact of different environments on individual tree growth. In this study, we constructed a comprehensive spatial structure grade index based on tree grading theory to judge the tree growth states in the stand and assign corresponding grades of 0 to 9 (FCGSS). The values exceeding nine were grouped into grade nine (Fig. 3 and Table 4). Individual trees were categorized into five levels: I (0–1), II (2–3), III (4–5), IV (6–7), and V (8–9).

$$FCGSS = 10 \cdot \frac{F_i - F_{\min}}{F_{\max} - F_{\min}} + \frac{1}{2} \tag{3}$$

2.3. Tree grading growth model

2.3.1. Basic growth model

The Richards growth equation is one of the most widely applied growth curve equations in modern forestry models due to its broad adaptability, reasonable analytical properties, and excellent fitting capabilities. The Richards growth equation is as follows:

$$Y = a[1 - exp(-kt)]^c \tag{4}$$

Where Y represents DBH; t represents age; a, k, c represents the fitted parameters.

2.3.2. Multi-grade morphological structure growth model

DBH, tree height, crown width, and under living branch height are the basic parameters of tree morphological structure. The growth model uses these parameters as prediction factors and constructs the growth model of DBH, tree height, crown width, and height under branches. The DBH calculation formula is as follows:

$$DBH = f_a(x)(1 - e^{-f_k(x)t})^{f_c(x)} \tag{5}$$

$$f_a(x) = bx^2 + cx + d \tag{6}$$

$$f_k(x) = A_1 + \frac{A_2}{w\sqrt{\frac{\pi}{2}}} e^{-2\left(\frac{x-x_0}{w}\right)^2} \tag{7}$$

$$f_c(x) = A_2 + \frac{A_1 - A_2}{1 + \left(\frac{x}{x_0}\right)^p} \tag{8}$$

The tree height, crown width, and under-living branch height calculation formula is as follows:

Table 3
Stand spatial structure index.

Index	Calculation Formula	Variable Definition	Description
Uniform angle	$W_i = \frac{1}{n}\sum_{j=1}^{n} Z_{ij}$	W_i is the uniform angle of central tree i. When the angle between central tree i and neighboring tree j is less than the standard angle, $Z_{ij} = 1$, otherwise, $Z_{ij} = 0$.	Uniform angle represents the spatial distribution pattern of trees in horizontal space, with random distribution values of (0.475, 0.517], uniform distribution of (0, 0.475], and clustered distribution of (0.517,1]. The larger the value of W_i, the more clustered the distribution of trees, and the greater the competition between adjacent trees.
DBH Dominance	$U_i = \frac{1}{n}\sum_{j=1}^{n} k_{ij}$	U_i is the neighborhood comparison of central tree i. When the DBH of neighboring tree j is smaller than that of central tree i, $k_{ij} = 0$, otherwise, $k_{ij} = 1$.	DBH dominance is a neighborhood-based competition index. It reflects the degree of differentiation of tree size. The values of U_i are mainly divided into four types: 0, 0.25, 0.75, and 1. The larger the value, the greater the degree of tree differentiation, and the greater the competitive pressure the tree bears. The competition between trees is an important reason for the differentiation of tree size.
Openness	$OP_i = \frac{1}{n}\sum_{j=1}^{n} \frac{D_{ij}}{H_j}$	OP_i is used to describe the condition of the individual tree growth space in the plot. D_{ij} is defined as the distance between the target tree i and the neighboring tree j. H_j is defined as the tree height of neighboring tree j.	The openness is a spatial structural parameter used to describe the light environment of trees within a forest stand. This parameter holds significant ecological significance.
Spatial density index	$D_i = 1 - \frac{r_i}{r_{max}}$	D_i refers to the degree of tree crowding in the spatial structure unit. r_i represents the minimum radius between the target tree and its 4 nearest neighboring trees, r_{max} is the maximum among all the minimum radius in the stand.	Due to the limitations of the Uniform angle in accurately reflecting the spatial density of trees in horizontal space, a spatial density index was proposed. A larger D_i value indicates a more crowded spatial structure unit formed by the central tree and neighboring trees in horizontal space.
The Hegyi competition index	$CI_i = \sum_{j=1}^{n} \frac{D_j}{D_i \bullet L_{ij}}$	CI_i refers to the degree of tree competition. D_i is the DBH of target tree i. D_j is the DBH of target tree j. L_{ij} is defined as the distance between the target tree i and the neighboring tree j.	The Hegyi competition index describes the competitive relationship between individual tree growth and their growth space. From the forest management perspective, maintaining the overall competition of the forest stand at a lower level is essential to enhance stand stability and spatial utilization capacity.
Forest layer index	$S_i = \frac{c_i}{3} \cdot \frac{1}{n}\sum_{j=1}^{n} x_{ij}$	S_i is is used to describe the vertical spatial distribution pattern of stand. When the central tree i and neighboring tree j are in the same forest layer, $x_{ij} = 0$, otherwise, $x_{ij} = 1$. c_i is the forest layer of the target tree i.	The Forest layer index not only reflects the vertical distribution pattern of multi-layered forests but also indicates the diversity of canopy structures within spatial structural units. A higher value indicates a more complex vertical spatial structure within the forest stand.

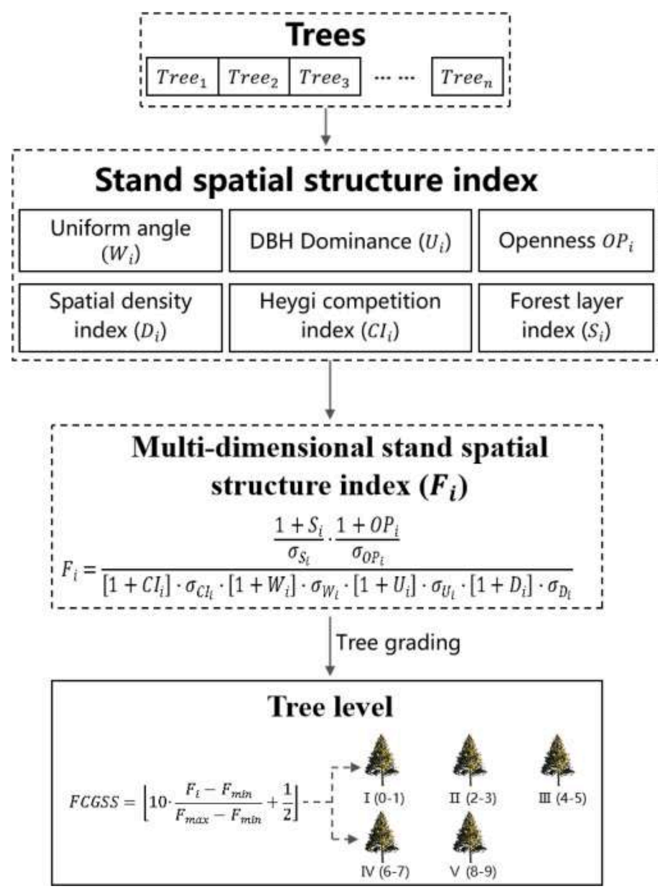

Fig. 3. The overflow of tree grading.

$$H = A_1 + \frac{A_2}{w\sqrt{\frac{\pi}{2}}} e^{-2\left(\frac{DBH - x_0}{w}\right)^2} \tag{9}$$

$$UBH = A_1 + \frac{A_2}{w\sqrt{\frac{\pi}{2}}} e^{-2\left(\frac{H - x_0}{w}\right)^2} \tag{10}$$

Table 4
Stand spatial structure evaluation level.

Stand overall spatial structure	Level
Spatial distribution is uneven, tree species composition is relatively simple, and tree competition is high in certain areas. The spatial structure is not ideal.	I(0–1)
A few spatial structure indices barely meet the standards. Tree species composition is relatively reasonable, with noticeable competition among trees, and the openness is relatively low.	II(2–3)
Overall, forest spatial structure indices are close to standard values, with various indices relatively balanced. However, optimization is still needed.	III (4–5)
Overall, the forest spatial structure is reasonable, with high species diversity, high species mixing, balanced canopy layer, favorable light conditions, lower spatial density index, and weaker competition.	IV (6–7)
The forest spatial structure is relatively ideal, with even tree distribution.	V(8–9)

$$CW = A_2 + \frac{A_1 - A_2}{1 + \left(\frac{H}{x_0}\right)^p} \tag{11}$$

Where DBH represents the diameter at breast height based on FCGSS, x represents the comprehensive grade value of spatial structure, t represents the individual tree age, and b, c, x_0, w, and A represent the fitted parameter values.

2.3.3. Bayesian method

The Bayesian method is a systematic approach developed based on Bayes' theorem to address and describe statistical problems effectively. A complete Bayesian analysis comprises data analysis, the construction of probability models, assumptions about prior information (prior distribution), the specification of effect functions, and final decision-making. The fundamental approach of Bayesian inference involves combining prior information with sample information. Subsequently, based on Bayes' theorem, one can derive posterior information and use it to infer the distribution of unknown parameters. Let $\theta = (\theta 1, \theta 2, \theta 3, \cdots)$ represent the parameter vector and $y = (y1, y2, y3, \cdots)$ represent the data vector. According to Bayesian theory, its basic formula is as follows:

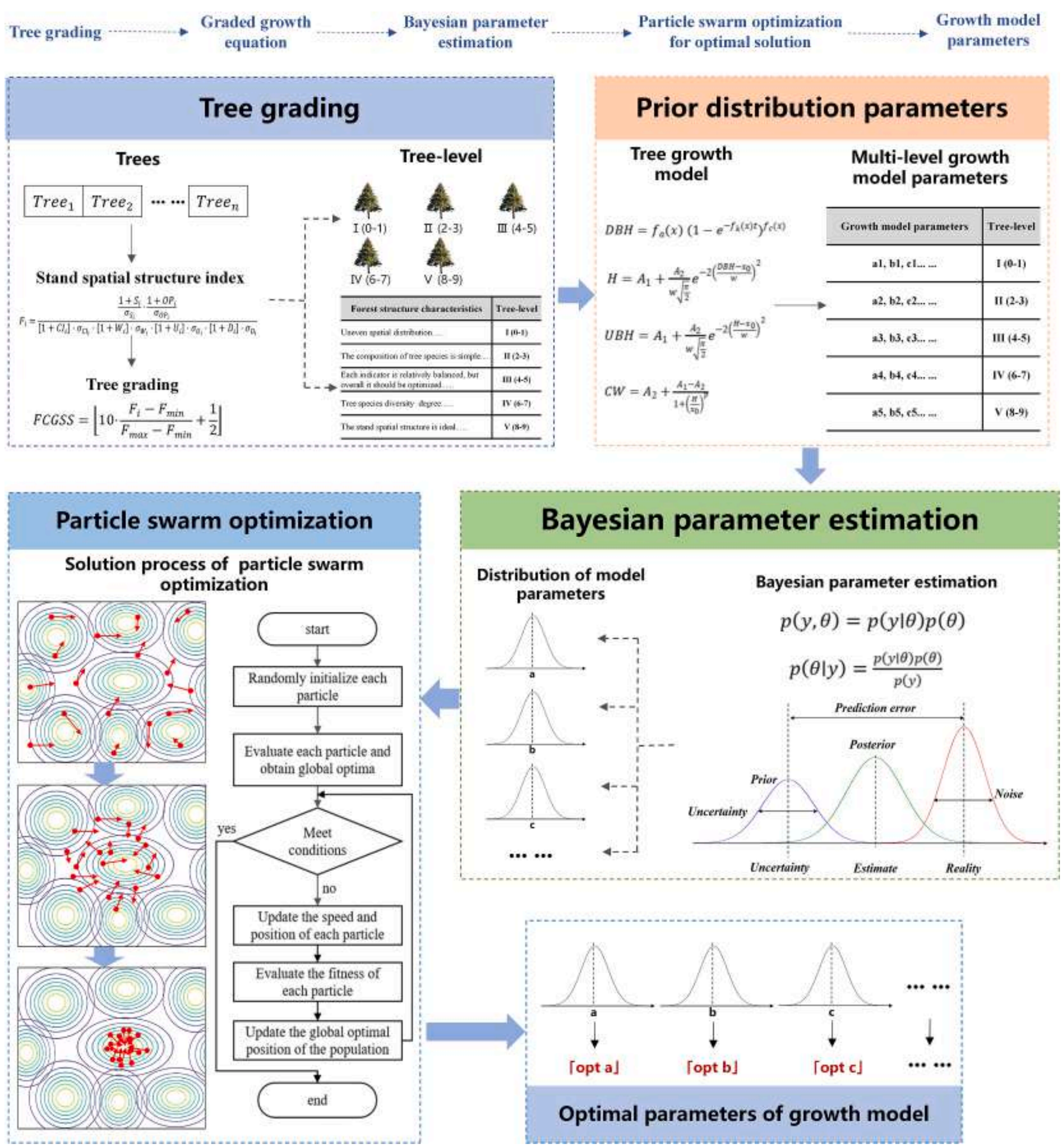

Fig. 4. The Construction workflow of grade growth model.

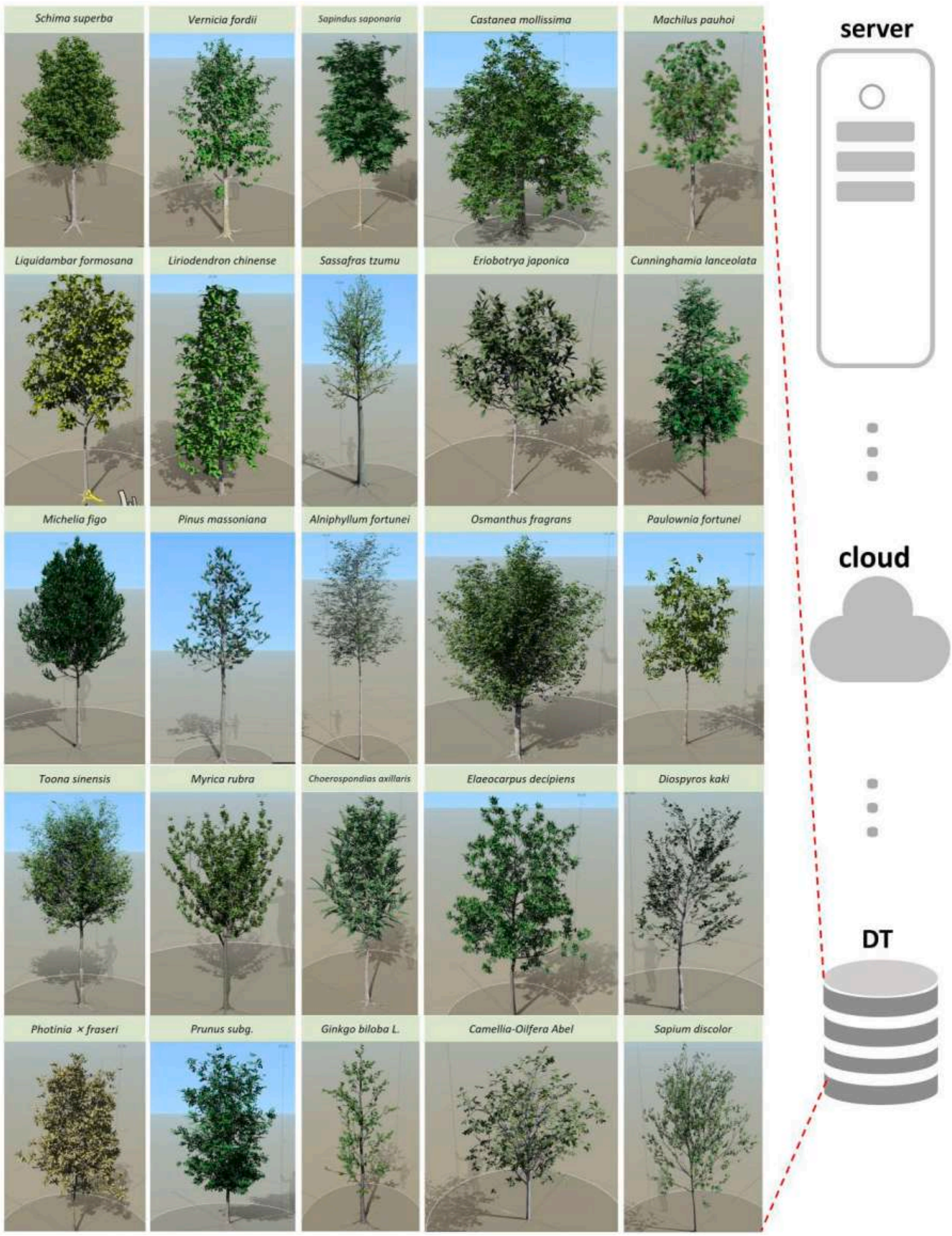

Fig. 5. 3D tree model database.

$$p(y,\theta) = p(y|\theta)p(\theta) = p(\theta|y)p(y) \tag{12}$$

Where p represents the probability distribution function or density function. In Bayesian methods, the uncertainty of parameter θ is described through probability distributions, and parameter estimation is performed accordingly. The conditional probability distribution can be expressed as follows:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \tag{13}$$

For continuous θ, $p(y) = E_\theta[p(y|\theta)] = \int p(y|\theta)p(\theta)d(\theta)$, $p(\theta|y)$ represents the posterior distribution of the desired parameters. $p(y|\theta)$ is the likelihood function of y given θ, and $p(\theta)$ is the prior distribution of θ.

2.3.4. *Construction of growth models based on Bayesian and grading theory*

In the mentioned growth equation for artificial Chinese fir, it is necessary to select appropriate prior distributions for parameters such as a, b, c, A1, and A2. These informative priors can be derived from historical literature or subjective beliefs. Many researchers tend to use non-

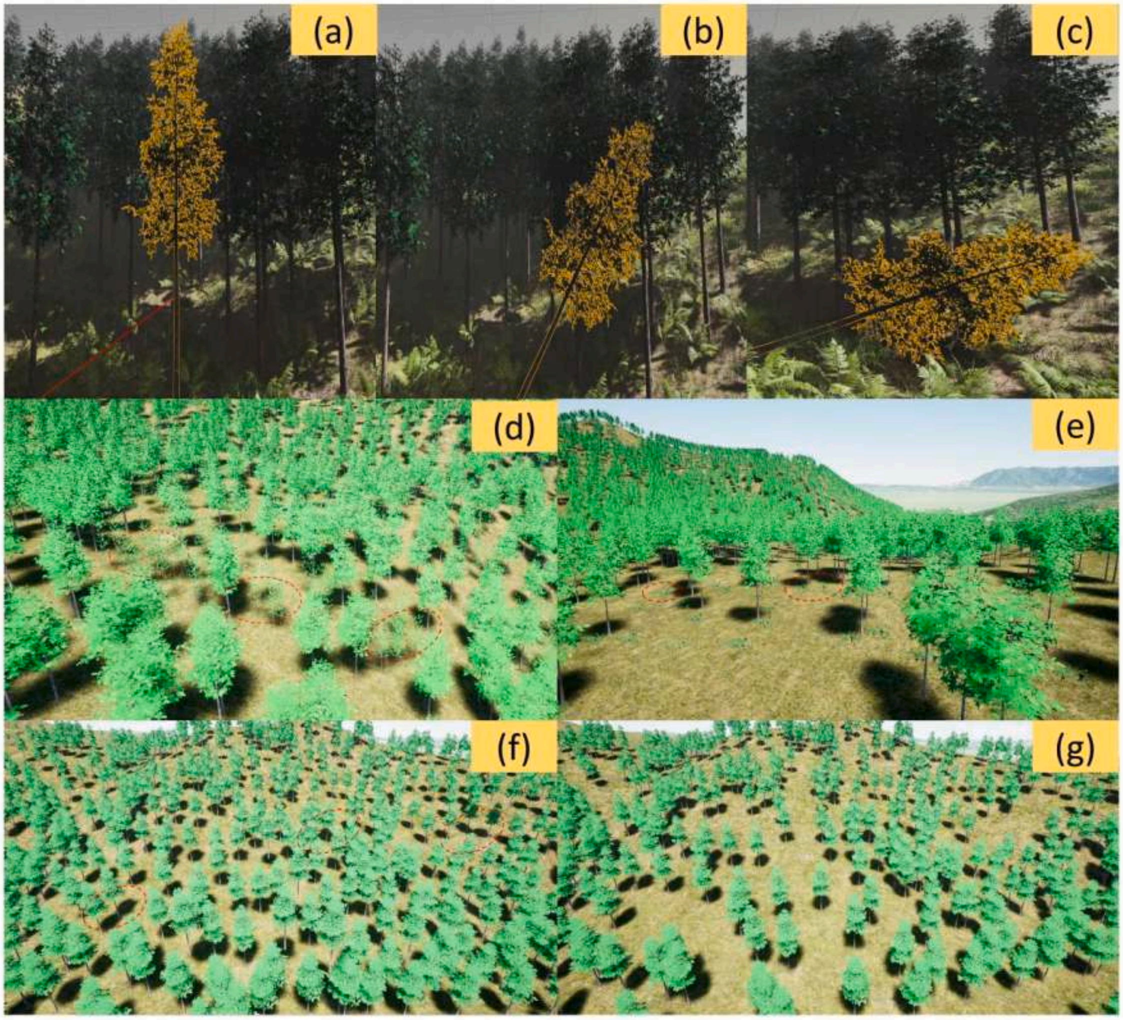

Fig. 6. Silvicultural measure in forest digital twin. (a)-(c) represents individual tree harvesting. (d) represents replanting measures. (e) represents pruning. (f)-(g) represents the scene before- and after-thinning, which is stand-level thinning.

informative prior distributions. In our study, we opt for informative prior distributions as part of the Bayesian approach. Informational priors can be determined based on the parameter estimates of the graded Chinese fir growth equations (I, II, III, IV, V) calculated earlier.

Subsequently, we employ the Particle Swarm Optimization (PSO) algorithm to explore the parameter space and obtain optimal parameters. In the PSO method, the parameters obtained through Bayesian estimation serve as initial estimates for the algorithm. Each particle represents a set of parameters (e.g., a, b, c), with each particle having a position and velocity. The algorithm updates the position of each particle based on its position and velocity and assesses the fitness (or objective function value) of each particle. In this study, fitness values are the fitting accuracy of the growth model.

The overall workflow of the growth model is depicted in Fig. 4. It involves tree grading, the construction of graded growth equations, Bayesian parameter estimation, and particle swarm optimization to seek the optimal solution and determine the best-fit parameters for the growth model.

2.4. Elements of the stand visualization

In this study, the forest digital twin uses Unreal Engine 4 (UE4) as a visualization platform (https://www.unrealengine.com). This study uses C++ and blueprints (visual programming methods) to visualize trees and stands. The forest digital twins are mainly divided into three parts: tree model database (Fig. 5), 3D Terrain, and dynamic interaction (Fig. 6).

Terrain data are indispensable in the digital twin of forestry. In our study, we use the remote sensing images and the terrain data from the study area as support to generate a real-world surface model. Then, we add the corresponding terrain material, road model, building model and other 3D models in landscape to increase the realistic degree of the forest digital twin surface environment.

In addition, we selected species with significant ecological, social and economic significance in the study area for tree modeling. The main species are Schima superba, Cunninghamia lanceolata and Machilus pauhoi. In this study, 3D models of more than 27 tree species were made as digital assets and connected to tree data. Each tree was assigned a unique identifier to facilitate our subsequent query and modify individual tree attribute information. Since the integration of the tree database and tree species 3D model, we can obtain further information on how tree height, diameter at breast height or stand structure indices will change over time.

The real-time interaction between physical entities and the forest digital twin can increase the user's immersion experience by operating the mouse, keyboard, VR helmet, and other devices. With the support of geometric models, logical models, remote sensing data, information models, and tree attributes, the forest digital twin system has the capability to monitor and visualize tree growth, thinning simulation, stand dynamics, and forest succession.

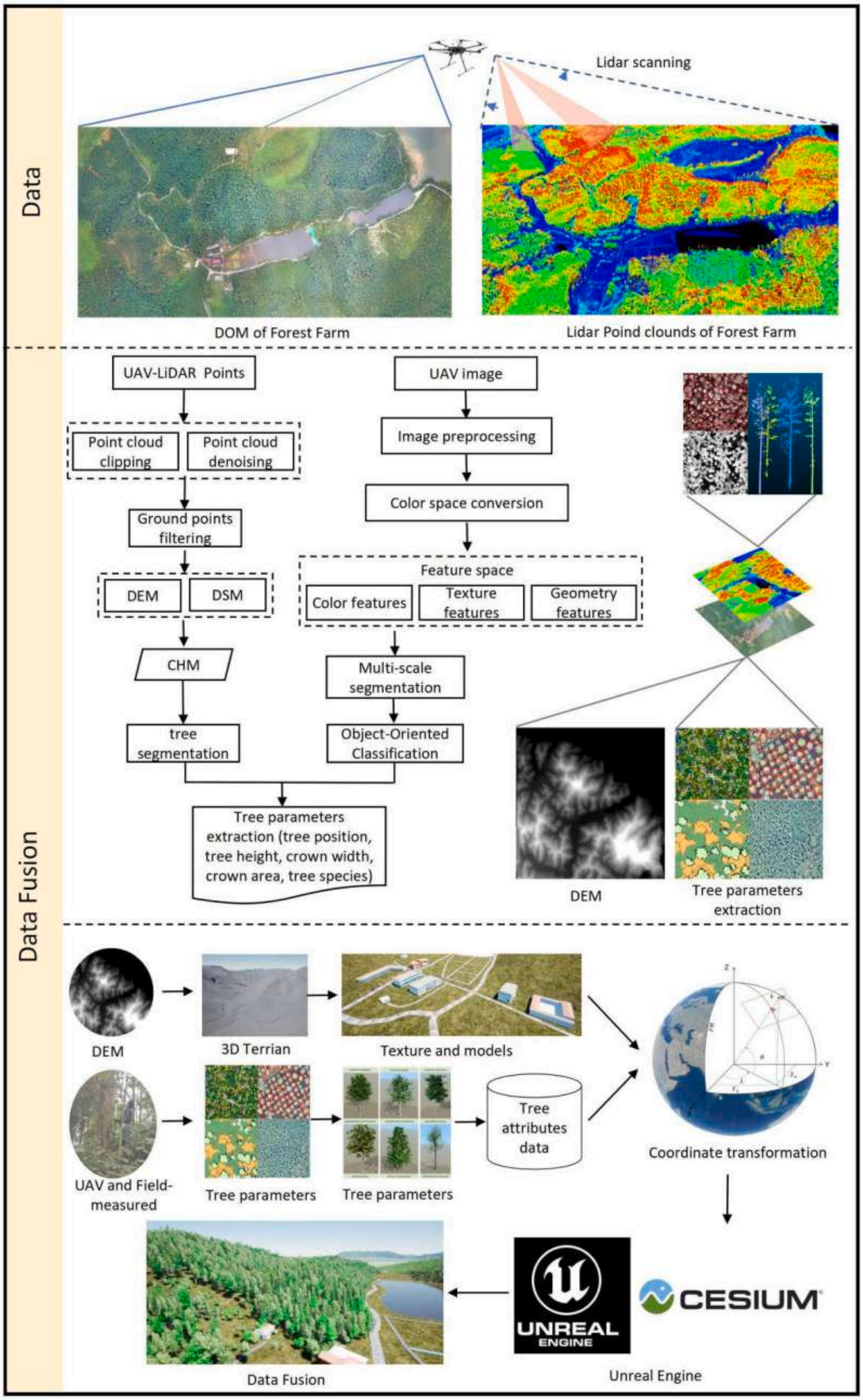

Fig. 7. The multi-source data fusion.

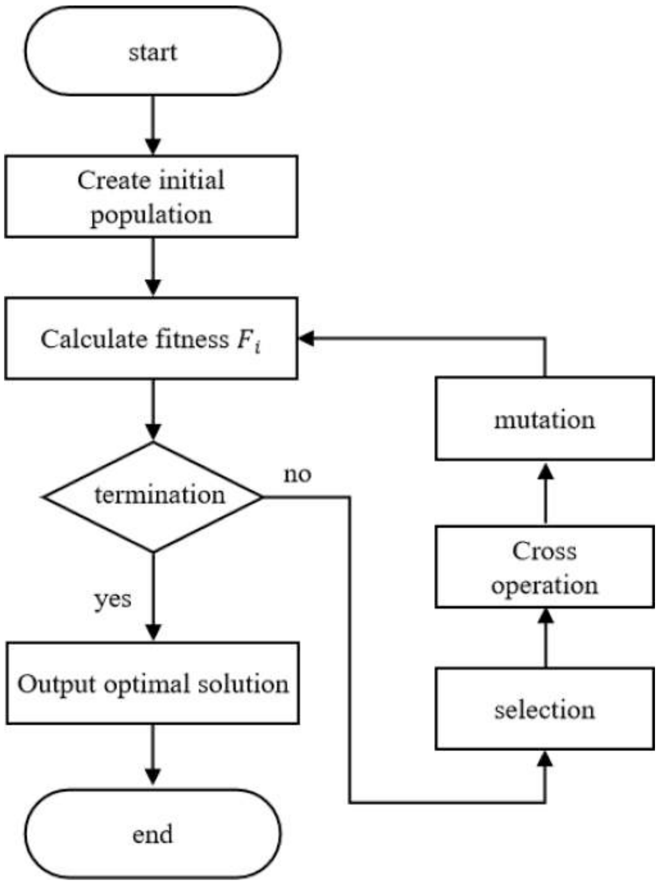

Fig. 8. The immune algorithm.

In summary, in the forest digital twin construction process, data fusion primarily includes data preprocessing, individual tree data extraction, 3D terrain fusion, coordinate transformation, loading forest sub-compartment data, 3D tree model database construction, and scene and tree growth model fusion (Fig. 7).

2.5. Construction of forest digital twin

2.5.1. Virtual-real synchronization and decision-making feedback

Thinning, as a silvicultural treatment in forest planning, the selection of harvested tree is limited by multiple factors, and multiple optimization objectives are often in conflict with each other, showing the characteristics of non-linearity and discontinuity. Therefore, multiple factors affecting stand structure need to be considered comprehensively in the selection process of harvested trees. The model output results in target trees that need to be regulated or that need to be removed to optimize the stand structure. For example, trees with larger U_i and larger W_i significantly affect the overall stand structure and need to be removed to optimize the stand structure. In this study, the immune algorithm, which is widely used in forest management and is relatively mature, was used to determine the harvested tree, F_i as a fitness function, CI_i, W_i, U_i, D_i, S_i, OP_i as the constraints of the algorithm to solve the harvested tree, and the immune algorithm algorithm is shown in Fig. 8.

$$\text{maximize}\, F_i = \frac{\frac{1+S_i}{\sigma_{S_i}} \cdot \frac{1+OP_i}{\sigma_{OP_i}}}{[1+CI_i]\cdot\sigma_{CI_i}\cdot[1+W_i]\cdot\sigma_{W_i}\cdot[1+U_i]\cdot\sigma_{U_i}\cdot[1+D_i]\cdot\sigma_{D_i}} \tag{14}$$

minimize.CI_i
minimize.W_i
minimize.U_i
minimize.D_i
maximize.S_i
maximize OP_i

$$s.t. 0 \le CI_i, W_i, U_i, D_i, S_i, OP_i \le 1$$

$$0.41 \le W_i \le 0.52$$

$$0.45 \le D_i \le 0.55$$

In the harvesting process, when a certain tree is harvested, the neighboring tree and its spatial structural unit also change, so it is necessary to determine the new harvested tree by calculating the F_i of retained trees until the harvesting intensity increases to the set value (Fig. 9). In this study, considering the balance between economic and ecological benefits, the number of selected harvested trees in the plot did not exceed 15 % of the total trees. The harvested tree selection steps are as follows:

(1) Construct a triangular network based on tree spatial coordinate locations to connect all the trees in the plot.
(2) Calculate the stand structure indexes such as uniform angle, DBH dominance, openness, spatial density index, the Hegyi competition index, forest layer index, and the F-index of each tree in the triangular network within the stand. Input the stand structure indices and tree ID into the immunization algorithm to solve the optimal set of solutions, and output the desired harvested tree ID.
(3) Analyze whether the harvesting intensity reaches the specified intensity, and if it does, stop harvesting. Otherwise, reconstruct the triangular network according to the spatial location of the retained trees in the plot and determine a new spatial structural unit.
(4) Repeat steps (2) to (3) until the harvesting intensity is reached to maximize the value of the overall F index.

The digital twin can calculate real-time structure indices before and after thinning. At the same time, by incorporating a growth model, the digital twin can display new forest structure information on the console and make individual tree growth predictions. Therefore, the entire operation cycle of the forest digital twin is repetitive, fully automated, and requires minimal user assistance, which is the basis of decision-making feedback.

2.5.2. Construction process of forest digital twin

In our study, we integrate texture pictures collected from plots, multi-temporal remote sensing data, and the Cesium Earth engine to construct forest digital twin terrain. Individual tree attribute information such as DS, H, UBH, and CW, combined with the Unreal Engine 4 and 3D tree species database, construct an interactive visualization scene of forest digital twins. The FDT can import physical world spatial position information, field-measured individual tree growth data and tree attribute data to update itself in real-time and drive FDT development. Forest digital twins can calculate the stand structure indices such as *W, U, OP, D, CI, S,* and *F*, and FCGSS index and divide the stand spatial structure index into grades 0–9.

Forest managers judge the stand quality and stand spatial distribution pattern based on the indices output from the calculation model. Forest managers can wear helmets to roam and interact in forest digital twins. They could use interactive devices such as spatial controllers and spatial handles to view individual tree attribute information and conduct forest management practices (tending, harvesting, regeneration, and replanting simulation). Forest managers can conduct tree-, stand-, or landscape-level thinning simulations as needed. The digital twin calculation module calculates the stand structure indices *W, U, OP, D, CI, S,* and *F* after thinning. The forest digital twin could give an initial judgment on the overall stand quality based on the F values, update the tree growth database and provide forest managers with real-time feedback information. Forest managers can give an overall evaluation based on the real-time output results from the forest digital twin and determine

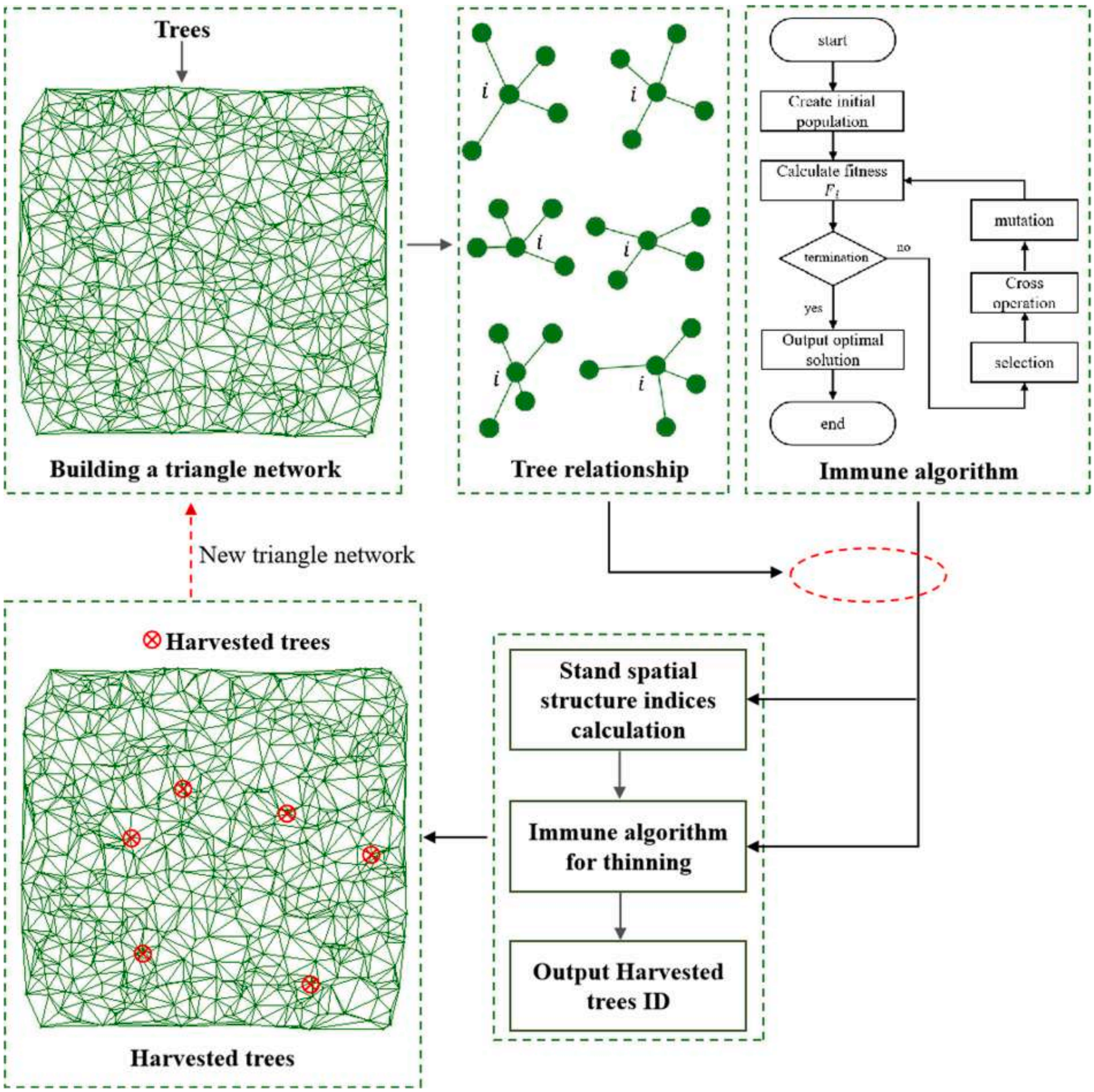

Fig. 9. The workflow of harvested tree selection.

whether simulated logging needs to continue. The console displays the parameter changes of individual trees, the overall stand structure and the thinning effects before and after intervention.

In summary, the forest digital twin can achieve real-time data updates, decision-making feedback, two-way interaction and automated processes. One forest manager can complete the entire operation process. The overall process is shown in Fig. 10.

2.6. Evaluation of virtual reality representativeness

To test the authenticity of the system, we conducted matching experiments. Images from 23 different locations within the natural plots were presented to evaluators. The evaluators' task was to wander through the forest digital twin and attempt to find the corresponding virtual forest structure in the forest digital twin. We checked whether the evaluators could match the real forest structure seen in the image with the virtual world in the forest digital twin. We recorded the number of attempts needed for successful recognition. The number of evaluators for the experiment was set to 6. In the representation experiment of the forest digital twin, evaluators were asked to match the real forest structure captured on 23 images with their virtual reality representation in the forest digital twin. The assessors have three attempts to match the real world with the digital twin forest structure. Otherwise, the identification is considered unsuccessful (Table 5). In addition, in order to scientifically and objectively evaluate the fitting effect and effectiveness of growth models, this study used mean absolute percentage error (MAPE), coefficient of determination (R^2), and accuracy (A) to evaluate the fitting accuracy and applicability of models for diameter at breast height, tree height, crown width, and under branch height.

3. Results

3.1. Forest digital twin representativeness

Table 6 shows the relative numbers of successful recognition attempts and absolute numbers per attempt needed. In most attempts, assessors can still accurately match the structure displayed on images with the real stand structure. Six evaluators had a lower success rate on

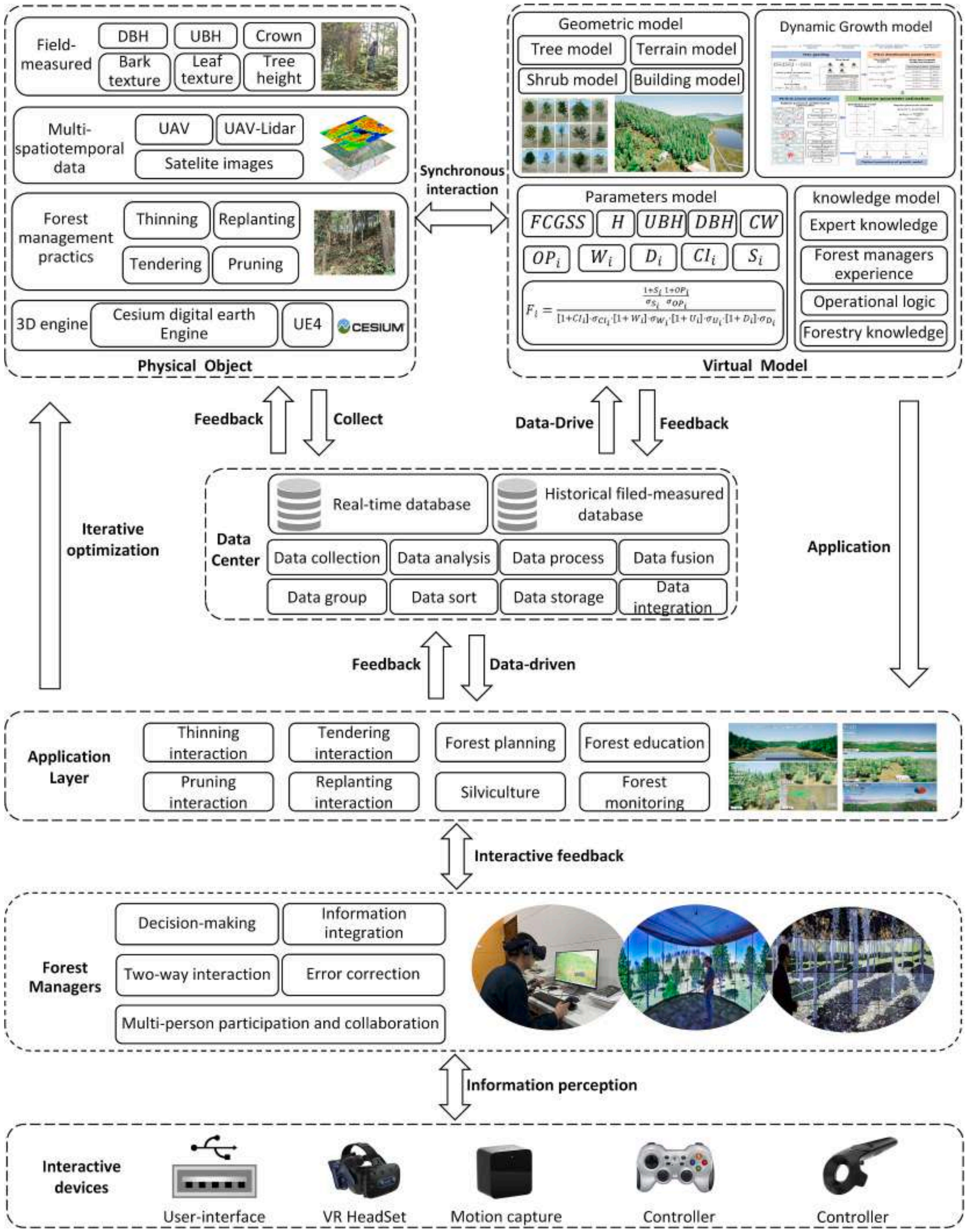

Fig. 10. The construction process of forest digital twin.

Table 5
Assessor information.

ID	Age	Sex	Educational background	Major	Profession	VR/XR familiarity	DT familiarity
1	41	Male	Undergraduate	Forestry	Engaged in research on the cultivation, processing, and utilization of plants	Low	Low
2	33	Male	Master	Geographic information science	Engaged in forest management planning and forest resource monitoring work	Middle	Low
3	51	Male	Associate College	Mechanical Automation	Surveillance and patrol, forest resource management, forest protection and fire prevention, cutting	Low	Low
4	29	Female	Doctor	Forestry	Engaged in research work related to ecological remote sensing, forest quality assessment, and data visualization analysis	Middle	Middle
5	27	Male	Master	Geographic information science	Combine forestry knowledge and geographic information to develop a digital twin system	High	High
6	19	Male	Undergraduate	Forestry	Learn forestry knowledge in school	High	Low

Table 6
Success in matching the images of the forest structure with their virtual reality representation in the forest digital twin.

Experiment Name	Relative (%) Absolute (n)	Successful identification			Unsuccessful identification	Total
		1st attempt	2nd attempt	3rd attempt		
Forest scene image VS. Forest digital Twin	(%)	57.24	22.46	11.60	8.70	100.00
	(n)	79	31	16	12	138

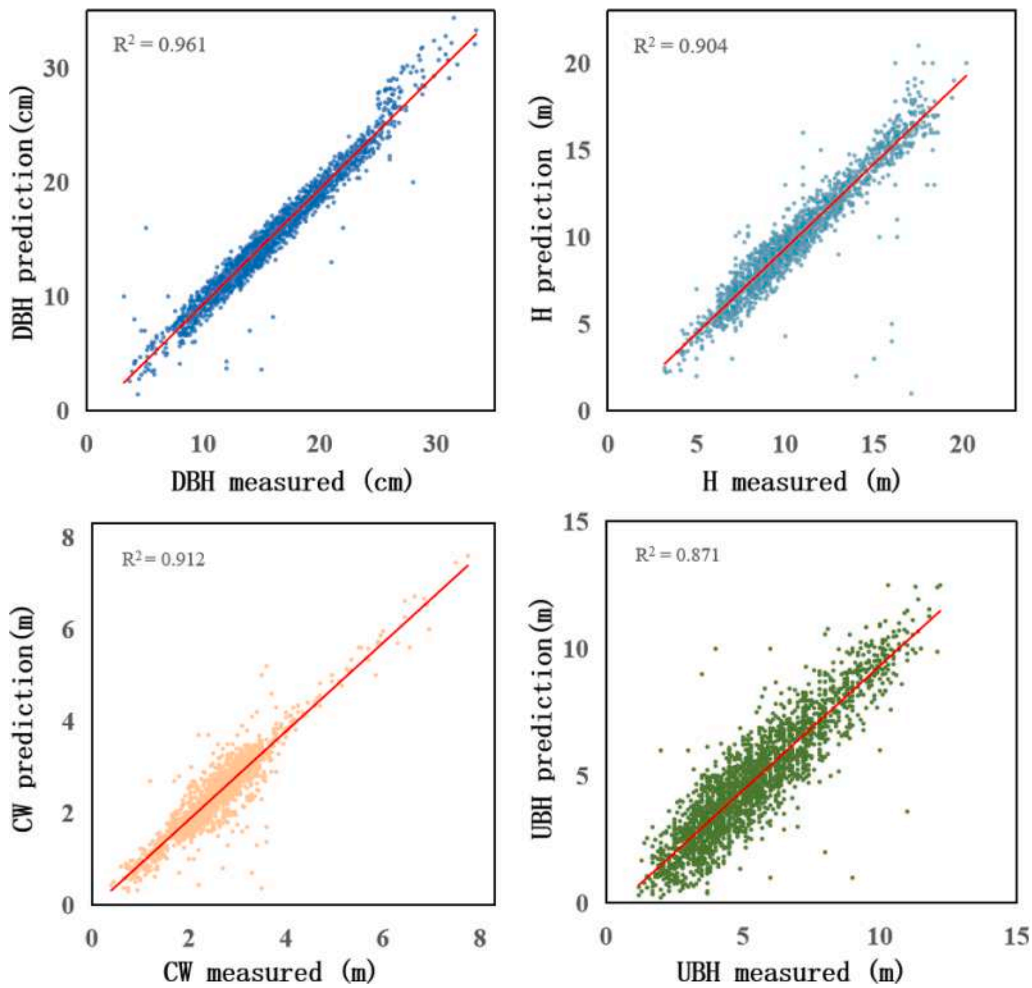

Fig. 11. The predicted values and field-measured values of DBH, H, CW, and UBH.

the first two attempts, and the recognition success attempts were 57.24 % and 22.46 %, respectively. The third attempt had a higher recognition success rate, with only 11.60 % attempts. The overall unsuccessful recognition attempts of all assessors was very low, at 8.7 %. The results indicate that the match between the forest structure seen on the image and the real forest structure is successful, the difference in recognition success rate is very small, and the forest digital twin could describe the real forest structure well.

In this study, the forest farm consisted of 13 forest sub-compartments, and the forest digital twin maximum loading capacity was nearly 100,000 trees. When conducting experiments on one sub-compartment, the image rendering is smooth, without any rendering problems or stagnation during movement. The experimental area or the number of trees greatly exceeds the requirements for thinning and pruning.

3.2. Dynamic tree growth model

The grading results indicated that III-, IV-, and V-level trees accounted for a larger proportion of the trees (Fig. 13). Among all levels, the UBH (24.3 %) had the lowest prediction accuracy, and the DBH (94.7 %) had the highest prediction accuracy. Fig. 12 illustrates that the fluctuations of the III-level and V-level are large, whereas the remaining levels exhibit minor fluctuations, with prediction accuracy of modelIexceeding 80 % or higher. The overall estimated accuracy across all five levels exhibits a fluctuating trend, initially declining and then rising with increasing levels (Fig. 11 and Fig. 12).

The prediction accuracy of the base DBH growth model is much less than that of the basic growth model, which is 0.572 (Table 7). The results indicated that the growth model proposed in this study exhibits a high degree of fitting for trees in different growth conditions (Fig. 11 and Fig. 12), especially for those facing limited growth space and intense competition (FCGSS = 0–4).

Table 8 shows that the tree grade growth model integrating Bayesian

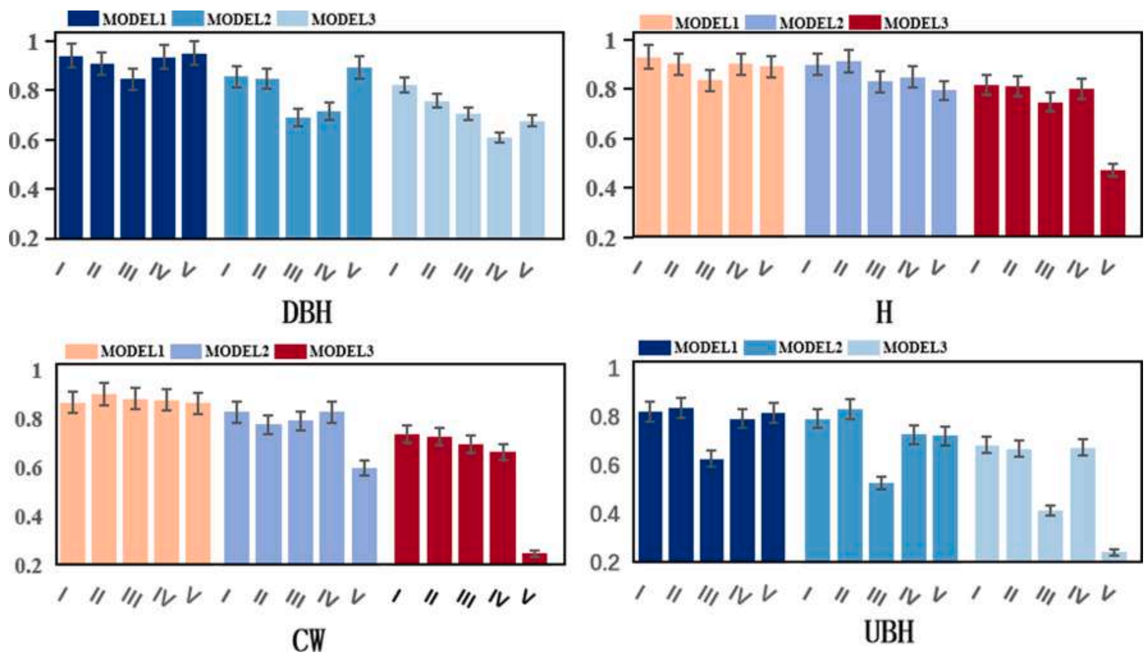

Fig. 12. Prediction accuracy of three growth models at different levels. MODEL1: TGGM; MODEL2: GCM; MODEL3: SSU.

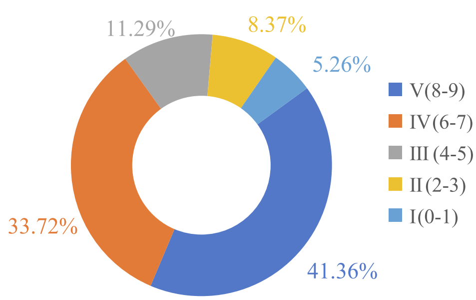

Fig. 13. Percentage of trees of different grades.

and PSO (TGGM) is superior to the basic tree grade growth model based on the single competitive index (GCM) and the spatial structure unit-based model (SSU). For DBH, H, UBH, and CW, under the TGGM model, the accuracy values (A) were as high as 94.70 %, 91.9 %, 84.6 %, and 89.9 %, respectively, which were slightly greater than those of the GCM model. However, they were much larger than the SSU model. The values of R^2 exhibited the same trend as A. At the same time, the MAPE values of the TGGM model were approximately 5.13 %-10.06 %, which were relatively lower than those of the SSU model.

3.3. Dynamic interactive thinning simulation

The thinning experiment verified the practical feasibility of the forest digital twin as an alternative or complementary tool for forest managers and decision-makers. The thinning simulation was performed by one assessor (ASS), forest digital twin itself (FDT), and assessor-forest digital twin interaction thinning as a reference (Fig. 14). The ASS, FDT, and ASS-FDT interaction thinning simulation starts from the same stand structure, and the individual tree selection and thinning approaches can be freely set in the forest digital twin according to user needs. Table 9 shows the changes in stand spatial structure before- and after-thinning. The results indicated that there were certain differences in the target tree selection under different approaches. Overall, there were more similarities. The ASS focuses on spatial density and competition when selecting the target tree. The magnitude of changes in various indices in FDT is relatively large after thinning. The overall results of FDT and ASS-FDT interaction thinning are comparable. Under the ASS-FDT approaches, the overall forest structure was greatly improved, with varying degrees of improvement in the uniform angle index, DBH dominance index, openness, spatial density index, Hegyi competition index, and forest layer index. The F index increased by 22.82 %, indicating that ASS-FDT interactive decision-making is of great help in improving the overall stand spatial structure. The ASS-FDT interaction thinning approaches well represent the desired thinning method.

Table 7
Parameters of the morphological growth model of Chinese fir.

Parameter	$f_a(x)$	$f_k(x)$	$f_c(x)$	*Y*	*DBH*	*H*	*UBH*	*CW*
a				32.347				
b	−3.109							
c	0.084			1.503				
d	37.993							
k				0.043				
A1		1.301	1.889			18.936	12.236	3.121
A2		40.001	0.701			103.017	69.313	1117.473
X0		3.571	0.473			13.772	10.007	431.572
w		25.002				10.005	8.103	
p			1.997					1.997
MAPE				17.96 %	5.43 %	7.94 %	10.06 %	5.13 %
A				0.572	0.947	0.919	0.846	0.899
R^2				0.497	0.961	0.904	0.871	0.912

Table 8
The performance of the TGGM, GCM, and SSU model.

Model name	Indicators	TGGM	GCM	SSU
DBH	MAPE	5.43 %	7.46 %	13.95 %
	A	0.947	0.914	0.648
	R^2	0.961	0.899	0.702
H	MAPE	7.94 %	8.66 %	10.87 %
	A	0.919	0.894	0.801
	R^2	0.904	0.877	0.829
UBH	MAPE	10.06 %	14.73 %	15.63 %
	A	0.846	0.793	0.602
	R^2	0.871	0.803	0.639
CW	MAPE	5.13 %	7.04 %	16.42 %
	A	0.899	0.881	0.664
	R^2	0.912	0.901	0.574

TGGM: tree grade growth model; GCM: basic tree grading growth model based on the single competitive index; SSU: spatial structure unit-based model.

4. Discussion

4.1. Utilization of forest digital twin

In our study, we constructed a forest digital twin by integrating 3D engine, spatio-temporal data, and intelligent interactive environment. We tried to build a virtual environment to visualize the real forest structure. From the perspective of Human-Computer, the level of FDT fidelity is the key factor to perform the visual interpretation, which has significant implications for users to execute the interaction actions. Based on this reason, we carried out virtual reality representativeness. Experiments have shown that assessors can match real forest images with virtual forest scenes of FDT well. In most attempts, Assessors had a lower success rate on the first two attempts, and the recognition success rate was relatively low. The third attempt had a higher recognition success rate. The overall successful recognition rate of all assessors was high. Forest digital twin visualization scenes composed of complex

Fig. 14. Dynamic interactive simulation.

Table 9
Changes in stand structure indices before and after thinning.

Assessors	Management	$\overline{W}$	$\overline{U}$	$\overline{OP}$	$\overline{D}$	$\overline{CI}$	$\overline{S}$	$\overline{F}$
ASS	Before-thinning	0.547	0.539	0.212	0.671	0.673	0.438	0.447
	After-thinning	0.533	0.518	0.227	0.533	0.587	0.441	0.498
	RIP(%)	2.56	3.90	7.08	20.57	12.78	0.68	11.41
FDT	Before-thinning	0.547	0.539	0.212	0.671	0.673	0.438	0.447
	After-thinning	0.506	0.502	0.236	0.524	0.571	0.469	0.506
	RIP(%)	7.50	6.86	11.32	21.91	15.16	7.08	13.20
ASS and FDT Interaction	Before-thinning	0.547	0.539	0.212	0.671	0.673	0.438	0.447
	After-thinning	0.496	0.497	0.263	0.517	0.561	0.502	0.549
	RIP(%)	9.32	7.79	24.06	22.95	16.64	14.61	22.82

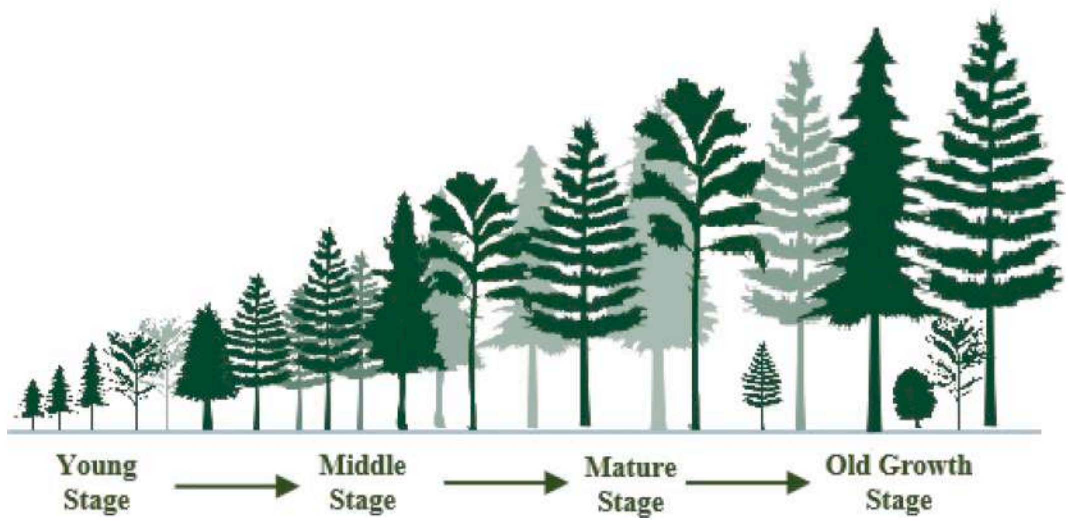

Fig. 15. Forest growth stages.

virtual geometrical models covered with appropriate textures perform better in guaranteeing visual similarity. Users could also capture the forest structure characterization from the FDT scene well.

Previous morphological growth model studies have mainly focused on simulating the stand average growth state by integrating single or multiple independent stand spatial structure parameters (Hu et al., 2023). This study constructed a comprehensive grade model of spatial structure to evaluate individual tree growth states. It combined Bayesian and PSO to develop a dynamic growth model to predict individual tree growth values. The growth model could utilize the prior distribution values to improve the growth prediction accuracy of DBH, H, CW, and UBH. The results indicated that the multi-grade growth model considers both stand spatial structure characteristics and individual tree physical attributes. The Bayesian-PSO combination effectively leverages prior information and sample data, yielding higher prediction accuracy and increased reliability.

Traditional forest management practice experiments are usually based on established permanent natural plots, such as thinning, silviculture and replanting. Forest managers could gain valuable knowledge and professional skills by marking activities (staining, scarification and tagging) and discussing with experts. However, forest managers are confronted with potential threats, such as the unknown changes in stand spatial structure parameters. They could not receive any positive or negative feedback on stand developmental changes after the natural or human-induced intervention (Fabrika et al., 2018). The forest digital twin could overcome some shortcomings of field-based experiments. Users were easier to operate in the virtual environment like in the real world. Therefore, the field-based forest management practices could also be performed in the forest digital twin, which makes the simulation means more abundant. For example, users can conduct thinning simulation experiments. They will have an immersive experience of forest development and changes in the future. Thinning experiments in forest digital twins will not be limited to the environments of permanent plots. Thinning experiments can be performed at any time and in various climatic conditions. The experimental results showed that there were certain differences in tree selection among the different approaches, but there were more overall similarities. The ASS focuses on spatial density and competition when selecting the target tree. Under the ASS-FDT approaches, the overall forest structure was greatly improved. Two-way interaction and real-time feedback create a new possibility for improving forest digital twin performance.

In addition, the integration of 3D simulation engine and spatio-temporal data are not coordinated. The combination of topography data, remote sensing images, UE, and 3D tree models is still in its infancy. It has several problems, such as inconsistent reference coordinate systems, difficulty in batch processing, and poor scalability. In this study, only six structure indices were set to grade the trees, and the six structure indices were mainly considered in terms of tree competition and stand density. The tree species were all Chinese fir, without considering the impact of tree species mixing, stand conditions, climate and other factors on tree growth, which resulted in poor expansion. The evaluators of the forest digital twin are 6 people, with a small number of samples, 23 scenarios that are more homogeneous, a lack of consideration for complex forests, and most of the evaluators are in the forestry industry, which is not conducive to the promotion of the digital twin. The tree model growth simulation parameter settings are relatively simple, simply setting the scaling ratio for the size. For the digital twin stress test, 100,000 trees were loaded, with little delay or lag, but for regional or national scale scenarios, the number of trees may reach hundreds of millions, and the construction of large-scale digital twins is still full of challenges. In addition, only 15 % of harvesting experiments were conducted, which is relatively single, and subsequent controlled harvesting simulation experiments with different intensities, such as 20 %, 30 %, 35 %, etc., can be carried out to improve the application scope of the forest digital twin. In the future, multi-agent models with autonomous perception and synchronization abilities could be the key to redefining the forest digital twin.

4.2. Implications for forest management practices

From the view of forest management practices, the forest digital twin can offer more opportunities because it has the ability of forest resource monitoring, analysis, and natural scene reproduction. First, the forest resource monitoring capability is accomplished owing to advanced equipment such as UAV and remote sensing satellites that record spatial and temporal changes in a forest on a regional scale. Collecting, returning, and processing forest resource data can be performed semi-automatically, benefiting from automated techniques and tools. The digital twin enables the visualization of forest management activities, forest disturbance, topography, stand structure, tree species composition, and public demands across time and space (Vagizov et al., 2021). Accordingly, forest managers, public officials, researchers, students, and volunteers can accurately capture the forest resource changes by tracking forest resource-affected areas.

Second, forests are more vulnerable to various hazards, and management investments are quite high. To avoid the occurrence of risks in the process of forest conversion (e.g., forest degradation, low forest productivity), simulations should be conducted on a small scale to

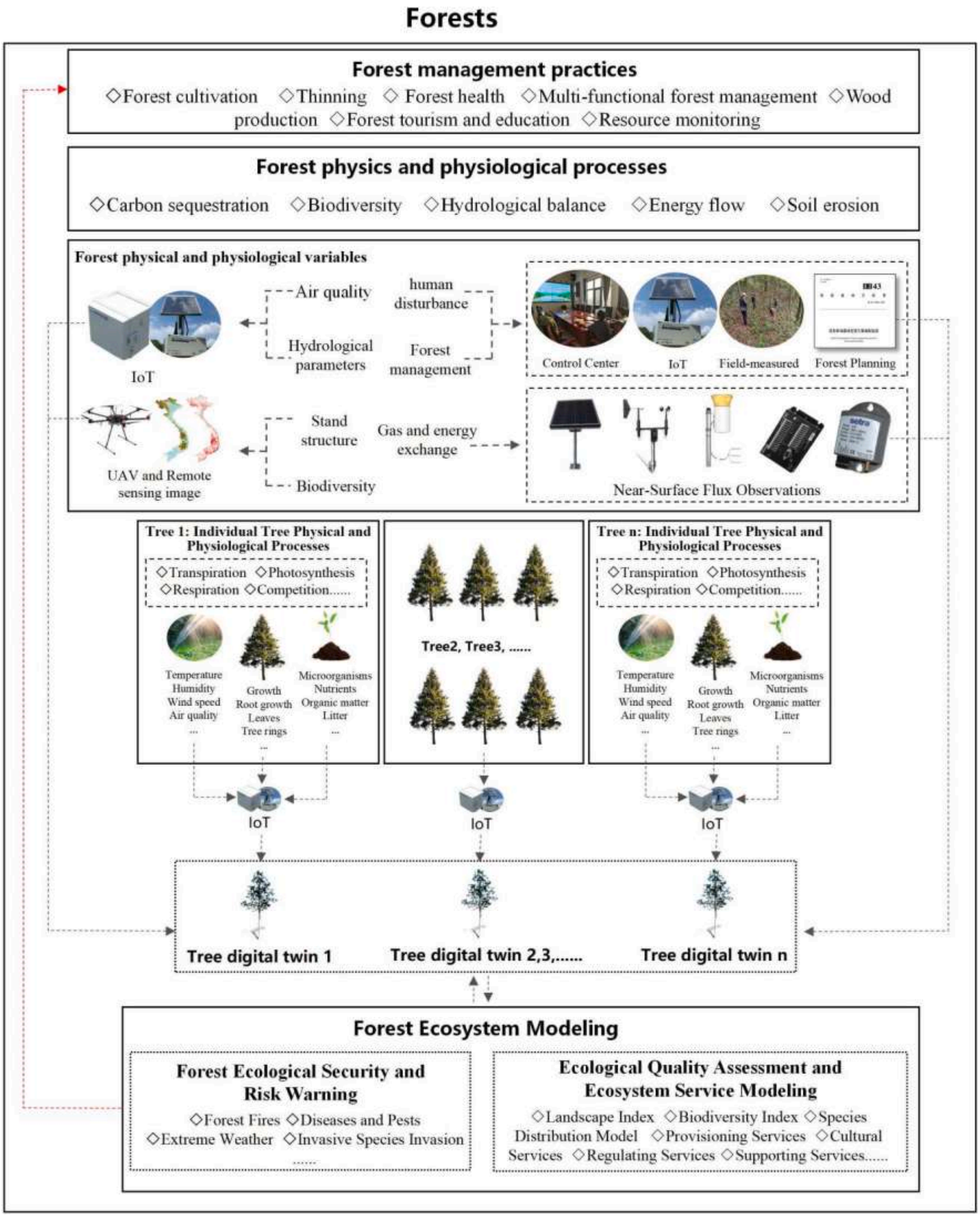

Fig. 16. Key design principles for forest digital twins.

accumulate experience. For example, integrating the physical and physiological processes of individual trees (e.g., evapotranspiration, photosynthesis, and hydrological balance) into the forest digital twin will probably help us to view and understand the mechanism of drought-induced tree mortality. Although many scholars have performed much research and achieved significant progress in modeling the process of tree mortality caused by extreme climate events (Choat et al., 2018), but the current research focuses on theoretical or mechanistic research (e.g., the response of trees to drought stress) and does not enable a 3D visualization or two-way online estimation of forest mortality events under the influence of extreme climate events. Forest digital twins can realize automated and integrated operation.

Forest growth, development, and succession are lengthy processes spanning several decades or centuries. Forest resource monitoring and forest management are also conducted in stages. Therefore, a forest digital twin differs from industrial, aviation, and urban digital twins because it does not require real-time synchronization of tree growth data in seconds, minutes, or hours. To ensure the timeliness of the forest digital twin, the frequency of data updates can be considered from four perspectives: growth stage, study scale, investigation factors, and unexpected events. For small-scale forest digital twins, forest resource data can be updated annually. Tree growth stages can be divided into four stages: the Young stage (a few years after seed germination), middle stage (lasting from a few years to several decades), mature stage (late stages of the life cycle), and old growth stage (Fig. 15). According to the tree growth characteristics, it is recommended to perform synchronous updates every 1–2 years from the Young to the Middle Stage, and every 5 years for other stages. In cases with no significant human or natural interference, data updates can be scheduled every 1–5 years. Real-time updates may be necessary if the forest is affected by extreme weather events or pest infestations.

Finally, for forest ecosystems, constructing a more complex and comprehensive forest digital twin should focus on tree attributes and their surrounding environment, physical and physiological processes of trees, model application, multi-source data fusion, forest risk prediction, and ecological quality assessment. Fig. 16 preliminarily demonstrates the basic elements needed and framework for forest digital twins (Buonocore et al., 2022).

5. Conclusion

Against the background of interdisciplinary convergence of forestry, GEO and information science, we proposed the forest digital twin to explore a new digital carrier of forest resources by integrating spatio-temporal data, 3D simulation engine, and intelligent interactive environment and forest management theory. The recognition matching experiments showed that forest digital twin could significantly characterize the real forest structure. The prediction accuracy of the tree grade growth model for DBH, H was more than 90.4 %, which can improve the forest digital twin prediction accuracy. The thinning simulation showed that the ASS-FDT interaction is superior to the assessors (ASS) and forest digital twin (FDT) for stand spatial structure overall optimization. The ASS-FDT strategy could enhance the overall stand spatial structure under the decision-making feedback and real-time interaction strategies. The research scope covered in our study was limited. In the future, our research will try to integrate forest vegetation coverage, forest resource utilization, and the impact of natural disasters on forest ecosystems into the forest digital twin.

CRediT authorship contribution statement

Hanqing Qiu: Conceptualization, Methodology, Software, Investigation, Formal analysis, Writing – original draft. **Huaiqing Zhang:** Conceptualization, Funding acquisition, Resources, Supervision, Writing – review & editing. **Kexin Lei:** Data curation. **Huacong Zhang:** Visualization, Investigation. **Xingtao Hu:** Resources, Supervision.

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

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2023.108416.

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