Crop 3D Reconstruction Techniques: Research Status and Prospects (Postprint)

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Abstract

In recent years, crop phenomics has witnessed substantial development driven by the widespread adoption of unmanned aerial vehicles (UAVs) and various sensors in crop breeding and field production. The advancement of crop phenomics and its associated technologies, characterized by high precision, high throughput, and high automation, has accelerated new variety breeding and optimized field management. Crop three-dimensional reconstruction technology represents one of the most fundamental methodological approaches in crop phenomics and serves as a crucial tool for accurately describing the holographic architecture of crop morphology. Three-dimensional reconstruction models of crops are of significant importance for high-throughput crop phenotyping, evaluation of plant architectural traits, and analysis of structure-phenotype correlations. To comprehensively summarize research progress on three-dimensional reconstruction technology in crop phenomics, this review examines three principal aspects: basic methodologies and application characteristics, current research status, and future prospects. Initially, this paper systematically categorizes existing crop three-dimensional reconstruction methods, reviews their fundamental principles, and analyzes their respective characteristics, advantages, and disadvantages. Furthermore, based on a generalized workflow for crop three-dimensional reconstruction methods, it investigates the applicability of each approach and delineates specific implementation procedures and considerations. Subsequently, according to different research targets, the applications of crop three-dimensional reconstruction are divided into three categories: individual plant reconstruction, field population reconstruction, and root system reconstruction. From these three perspectives, the paper reviews the application status of crop three-dimensional reconstruction technology. By evaluating accuracy, speed, and cost, it explores the current research status of various methods for three-dimensional reconstruction of different crops and identifies existing

problems and challenges within different reconstruction contexts. Finally, the paper provides an outlook on the future prospects of crop three-dimensional reconstruction technology from the perspectives of full-process automation, 4D phenotyping construction, crop virtual growth and simulated breeding, and the development of smart agriculture.

Full Text

Research Advances and Prospects of Crop 3D Reconstruction Technology

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Abstract: In recent years, crop phenomics has experienced tremendous development with the widespread adoption of unmanned aerial vehicles and various sensors in crop breeding and field production. The advancement of crop phenomics and related technologies, characterized by high precision, high throughput, and high automation, has accelerated the breeding of new varieties and optimized field management. Crop 3D reconstruction technology is one of the most fundamental techniques in crop phenomics and serves as a crucial tool for accurately describing the holographic structure of crop morphology. 3D reconstruction models of crops are significant for high-throughput phenotypic acquisition, evaluation of plant architectural traits, and analysis of correlations between plant structure and phenotype. To comprehensively summarize research progress in 3D reconstruction technology for crop phenotyping, this review examines three aspects: basic methods and application characteristics, current research status, and future prospects. First, we summarize existing crop 3D reconstruction methods, review their underlying principles, analyze the characteristics, advantages, and disadvantages of each approach, discuss the applicability of various methods based on the general workflow of crop 3D reconstruction, and outline specific procedures and considerations for implementation. Second, we categorize crop 3D reconstruction applications into three parts—single-plant reconstruction, field population reconstruction, and root system reconstruction—and review the application status from these three perspectives. Based on accuracy, speed, and cost, we explore the current research status of each method for different crop 3D reconstruction scenarios and identify existing problems and challenges under different reconstruction contexts. Finally, we analyze future prospects for crop 3D reconstruction technology.

Keywords: crops; 3D reconstruction; phenomics; crop root system; 3D scanner

1 Introduction

Morphological characteristics during crop growth and development are indispensable information in crop breeding research and field production management. Traditional acquisition of crop morphological information was performed manually, which suffered from a series of problems including high error rates, significant measurement errors, and time-consuming processes, creating obstacles for accelerating breeding progress and optimizing field management. The development of modern science and technology, particularly advances in sensor technology and computer vision, has made it possible to obtain morphological trait information through high-throughput, high-precision, and highly automated methods, with crop 3D reconstruction technology representing one of the important technical means to achieve this possibility.

3D reconstruction technology is a virtual reality technique that involves a series of processes including data acquisition, preprocessing, point cloud registration, data fusion, and texture mapping to virtually reconstruct real objects in computers. Although widely applied in industrial and medical fields with substantial societal value, its development in agriculture has been relatively slow due to constraints from field conditions, object complexity, and high costs. However, recent rapid developments in sensor technology and computer vision have significantly reduced equipment costs while enabling high-precision reconstruction algorithms adaptable to complex environments and scenarios, gradually expanding exploration and research in crop 3D reconstruction across different agricultural contexts. As of September 9, 2021, a Web of Science search using "crop 3d reconstruction" as keywords yielded 383 journal articles, with 316 published in the last five years, indicating that research in crop 3D reconstruction and related fields has been extremely active in recent years.

Previous studies by Zhang et al. [?], Liu et al.. [?], Li [?], Li et al. [?], and Wulder et al. [?] have summarized and analyzed crop 3D reconstruction methods, reviewing the classification, principles, and applications of these methods. However, none have systematically analyzed the characteristics of various methods. To investigate the applicability of different methods for 3D reconstruction of single plants, field populations, and crop root systems, this paper first reviews the classification and basic workflow of crop 3D reconstruction methods, summarizes the features of various reconstruction approaches, and compares their advantages and disadvantages. Subsequently, we review research progress in 3D reconstruction of single plants (maize, soybean, wheat, cotton, rice, rapeseed, tomato, etc.), field populations, and crop root systems, identify existing problems and challenges, and finally discuss future application prospects for 3D reconstruction technology.

2 Crop 3D Reconstruction Methods

Crop 3D reconstruction refers to modeling and visualizing the overall morphology and topological structure of plants using computer graphics and machine vision methods. Due to significant differences in growth environments and physiological characteristics among various crops, their morphological topological structures also vary considerably, making the establishment of accurate crop 3D morphological models a long-standing research focus in agronomy and computer graphics [**?**].

2.1 Classification and Basic Workflow of Crop 3D Reconstruction Methods

Based on sampling and reconstruction approaches, crop 3D reconstruction can be broadly categorized into four types: rule-based methods, image-based methods, 3D scanner-based methods, and digitizer-based methods [**?**, **?**], as shown in [Figure 1: see original paper]. Each method follows different data acquisition, processing, and modeling workflows. This paper analyzes the workflows and primary theoretical tools of different methods and summarizes a universal general approach for crop 3D reconstruction.

Current research on crop 3D reconstruction primarily involves three steps: first, determining the reconstruction target, including the whole plant or major organs; second, selecting information acquisition methods and 3D reconstruction approaches for target plants; and third, extracting corresponding plant model parameters through 3D reconstruction for application in precision agricultural management. The basic workflow of crop 3D reconstruction is illustrated in [Figure 2: see original paper].

2.1.1 Rule-Based Methods Rule-based methods analyze the topological structure and geometric morphological variation patterns during actual plant growth and development through dynamic structural models. These methods can be applied both in the field and laboratory settings. For specific plant species, model parameters can be altered to generate various growth morphological structures. The most commonly used dynamic structural models are L-systems [**?**] and automaton models [**?**, **?**]. These methods can vividly reflect crop growth topological structures and allow structural morphology adjustment through parameter changes. However, they are relatively complex and prone to errors due to human factors during application, resulting in reconstructed morphological structures that may significantly deviate from actual crop growth topology.

The workflow of rule-based methods mainly includes data acquisition, processing, 3D reconstruction method selection, and phenotypic extraction. In recent years, cameras or 3D digitizers have been increasingly used for data acquisition, reducing workload to some extent. Data processing varies depending on the acquisition method. The basic workflow of rule-based methods is shown in [Figure

3: see original paper].

2.1.2 Image-Based Methods Image-based methods obtain 2D images of target plants using cameras, preprocess the images through image recognition and processing techniques, and then achieve 3D reconstruction using pattern recognition and machine vision methods. These systems can be categorized into monocular, binocular, and multi-view vision systems. Monocular vision systems typically require ideal conditions and yield average reconstruction effects and precision, resulting in minimal application in plant 3D reconstruction [?]. Binocular and multi-view vision systems are currently more commonly used. Key technologies in binocular stereo vision spatial positioning include image acquisition, camera calibration, image preprocessing, edge feature extraction, and stereo matching [?]. Multi-view vision systems build upon binocular vision by adding multiple cameras to avoid occlusion problems caused by increased baseline distance.

Nguyen et al. [?] described a field 3D reconstruction system for plant phenotyping that successfully obtained plant canopy geometric morphological features using synchronized, multi-view, high-resolution color digital images for authentic 3D reconstruction of crops. Image-based methods can acquire detailed plant information and extract phenotypic parameters through relevant algorithms. For single-plant 3D reconstruction, these methods are suitable for well-lit, wind-free laboratory environments [?, ?]. For studying overall canopy volume, 3D reconstruction can also be performed in field environments [?, ?].

Due to their characteristics of simple equipment requirements, rapid and effective model establishment, and minimal human interaction, image-based methods have become a research hotspot in computer vision and computer graphics [?]. [Figure 4: see original paper] shows the workflow of image-based crop 3D reconstruction, while [Figure 5: see original paper] illustrates the soybean 3D reconstruction process based on images.

2.1.3 Instrument-Based Methods Instrument-based methods currently refer primarily to 3D reconstruction using 3D scanners and 3D digitizers. The 3D scanner-based method involves scanning entire plants on sampling platforms to obtain comprehensive 3D positional information of the whole plant. 3D scanners are currently the most widely used instruments in crop 3D reconstruction [?]. For example, Lee and Ehsani [?] used scanning technology to quantify citrus tree phenotypic parameters. Raumonen et al. [?] achieved tree canopy parameter acquisition and 3D reconstruction using scanners. Paulus et al. [?] studied the use of high-precision laser scanners with movable joint measurement arms to directly obtain non-invasive 3D data at sub-millimeter scales. Omasa and Konishi [?] utilized 3D lidar imaging technology to estimate plant characteristics such as canopy height, structure, carbon storage, and species, evaluating plant growth and morphology by reviewing lidar system development and applications from leaf to canopy remote sensing.

3D digitizers are increasingly applied in agriculture, primarily consisting of probes, scanning devices, and processing software that can rapidly acquire 3D spatial morphological coordinates of target plants and perform 3D reconstruction using corresponding software [?, ?]. The basic workflow for instrument-based crop 3D reconstruction is shown in [Figure 6: see original paper].

Both 3D scanner-based and digitizer-based methods offer rapid data acquisition, are non-destructive to plants, and generate large volumes of 3D point cloud data that preserve color and texture information with high fidelity. However, 3D scanners produce massive point cloud datasets that are relatively time-consuming to process, and the equipment is expensive [?]. Both methods also have high environmental requirements; particularly, laser scanners cannot have metal objects near the laser emitter during scanning and work best in dark rooms. Even for field reconstruction, closed environments are required, limiting their application to some extent. Additionally, raw 3D point cloud data obtained from scanners and digitizers contain substantial redundant and irrelevant information requiring processing. Fang et al. [?] placed plants in open spaces to achieve spatial discontinuity between target point clouds and invalid data, then applied threshold segmentation methods to separate target point clouds from background noise.

Currently, 3D information acquisition instruments have become increasingly economical and efficient, providing new opportunities for more effective agricultural practices through advanced equipment.

2.2 Characteristics Analysis of Crop 3D Reconstruction Methods

Summarizing the above review content, the characteristics of various methods are compiled in . Analysis of extensive literature reveals that: (1) The core of rule-based crop 3D reconstruction methods is dynamic models, which require minimal or manual sampling, generally achieving fast reconstruction speeds even for complex rules or models. However, reconstruction models overly dependent on algorithms and rules have lower precision, though they are less affected by environmental conditions. (2) Image-based 3D reconstruction methods sample using visual sensors such as cameras. Despite requiring numerous images, sampling is relatively fast. However, preprocessing time is lengthy due to the need for denoising and purifying target objects, and the 3D model generation algorithms must process large image volumes simultaneously, resulting in moderate reconstruction speeds. These methods are significantly affected by ambient light and background complexity. (3) Among instrument-based 3D reconstruction methods, 3D scanners and digitizers differ considerably. The former primarily uses position sensors or lidar as sampling devices with fast sampling speeds, while the latter uses contact sensors with slower sampling speeds. 3D scanners offer faster reconstruction speeds than digitizers, which have slower overall reconstruction due to complex usage and measurement processes. 3D scanners have lower reconstruction precision than digitizers, whose results are still considered the gold standard for crop 3D reconstruction. The advantages and disadvantages of these three method categories are summarized in .

3 Application Research on Major Crop 3D Reconstruction Technologies

Crop 3D reconstruction technology can be categorized by application target into single-plant 3D reconstruction (above-ground individual plants), field population 3D reconstruction (above-ground populations), and crop root system 3D reconstruction (below-ground root systems). Single-plant reconstruction focuses on detailed construction of crop morphological structures, generating point cloud models at the million-point level primarily for analyzing fine-scale phenotypic data such as leaf area, leaf angle, leaf width, leaf length, plant height, and internode spacing. Field population 3D models target field populations to obtain canopy-level phenotypes such as leaf area, leaf area index, leaf angle, canopy width, and canopy height. Root system 3D reconstruction aims to acquire root-related phenotypes and study root architecture, which is more complex than conventional above-ground reconstruction due to root invisibility in standard soil media, often requiring CT or MRI assistance. Based on references [?], the specific division of crop 3D reconstruction applications is shown in [Figure 7: see original paper].

3.1 Single-Plant Crop 3D Reconstruction

3.1.1 Research Status Single-plant crop 3D reconstruction is an important information technology for non-destructive study of individual plant morphological structure and growth patterns. Phenotype acquisition based on 3D models not only provides crucial data support for association analysis between molecular and phenotypic traits but also serves as the prerequisite and foundation for other applications. Single-plant 3D reconstruction is the most basic problem in crop 3D reconstruction, with analysis of single-plant 3D models providing important information for studying crop morphological development and plant architecture, as well as essential data foundations for crop growth simulation and virtual breeding.

This section summarizes research progress in 3D reconstruction of single plants including maize, soybean, wheat, cotton, rice, rapeseed, tomato, and other crops, detailing the hardware and software systems of corresponding 3D reconstruction methods and analyzing and comparing the advantages and disadvantages of different approaches. Specific details are provided in .

Overall, research before 2010 predominantly employed rule-based methods. After 2010, binocular and multi-view vision systems became increasingly popular with advances in computer technology and algorithms. Since 2015, integrated 3D scanners with combined acquisition and reconstruction functions have been increasingly adopted, representing an important process for simplifying reconstruction procedures and promoting technology popularization.

3.1.2 Problems and Challenges Currently, crop 3D reconstruction under different contexts still faces numerous problems and challenges. This section summarizes existing issues and challenges for maize, soybean, wheat, cotton, rice, rapeseed, tomato, and other single-plant crops.

(1) Maize. The canopy structure and spatial distribution of maize leaves affect CO_2 transport and light interception capacity within the canopy, significantly influencing growth, stress resistance, and yield. Therefore, selecting an efficient and accurate method for acquiring and reconstructing maize 3D morphological structure is crucial for precision maize management. Primary methods include rule-based, image-based, and 3D scanner-based approaches. Due to maize' s tall stature, calibration positions of binocular and multi-view vision systems are affected, leading most experiments to adopt 3D scanners for plant reconstruction. However, problems remain regarding time-consuming experiments, expensive equipment, and high environmental requirements.

(2) Soybean. Soybean production is a population-based process, with population structure directly affecting final yield. One major challenge in precision soybean management is obtaining accurate 3D morphological structures during growth to provide a foundation for improving soybean yield. Due to complex plant architecture and dense leaves and flowers, domestic and international research on soybean 3D reconstruction remains limited, representing a current research challenge. Various methods have been attempted, but none have demonstrated clear advantages for soybean reconstruction. Most studies use rule-based methods with extensive measured plant information to establish growth models, though reconstructed morphological structures often show significant errors compared to actual plants. [Figure 8: see original paper] shows a set of single soybean plant 3D reconstruction results.

(3) Wheat. As the world' s second-largest food crop, wheat presents significant challenges for 3D reconstruction and visualization due to its complex structural characteristics including tillering and leaf curvature, combined with environmental influences during growth and substantial morphological differences across growth stages. Wheat 3D reconstruction primarily employs rule-based and image-based methods, mainly because wheat plants are relatively short with simple structures. For example, Kempthorne et al. [**?**] developed a novel parametric technique that transforms raw manual measurement data and uses finite element methods to represent surfaces as linear combinations of compactly supported shape functions, enabling surface fitting using discrete smoothing D^2-spline surfaces in a new parameter space to achieve virtual representation of wheat leaves, as shown in [Figure 9: see original paper].

(4) Cotton. As a major cotton producer, China faces the challenge of improving cotton yield while ensuring quality. Cotton 3D reconstruction predominantly uses rule-based and image-based methods, though reconstructed morphological structures often contain errors compared to actual crop topology. [Figure 10: see original paper] shows cotton plant 3D reconstruction results.

(5) Rice. Rice holds important economic status in China as an irreplaceable food crop [**?**]. Virtual rice research through computer simulation of growth and development establishes 3D visual models combining morphological structure with physiological and ecological processes, playing important roles in yield improvement and ecological enhancement. Before 2010, rice reconstruction primarily used rule-based methods, while after 2010, image-based methods (binocular or multi-view vision systems) became more common. Current domestic and international research increasingly employs various methods including rule-based, image-based, and 3D scanner-based approaches, such as the rice 3D reconstruction using lidar shown in [Figure 11: see original paper]. However, all methods have limitations, and difficulties in data processing due to rice growth environments persist.

(6) Rapeseed. As a typical modern agricultural product rich in vitamins and nutrients [?], rapeseed has received increasing attention for virtual reconstruction with advances in computer graphics [?]. Rule-based methods and 3D scanners are commonly used for rapeseed 3D reconstruction, though data extraction remains time-consuming and equipment costs are high.

(7) Tomato. With high nutritional value, tomatoes have gained popularity [?]. Researchers increasingly combine computer graphics with agronomy for virtual tomato studies to improve yield and quality, shorten research cycles, and simulate environmental impacts on tomato production. However, due to tomatoes' complex growth structures, domestic literature on tomato 3D reconstruction remains limited, lacking a solid research foundation.

(8) Other crops. Other crops involved in 3D reconstruction research include strawberry, cucumber, pepper, grape, lettuce, and tobacco. Due to limited research, each method applied has certain limitations.

3.2 Field Population Crop 3D Reconstruction

Establishing 3D models of field crop populations is crucial for automated high-throughput phenotyping and for studying crop growth patterns and population structural characteristics. Moreno et al. [?] used lidar technology to reconstruct grape populations and proposed a biomass estimation method based on reconstruction that showed good results compared to manual measurements. Zhu et al. [?] tracked and reconstructed soybean and maize field populations throughout the entire growth period using multi-view vision technology, obtaining basic phenotypes including leaf length, leaf width, plant height, and leaf area. Based on the reconstructed full-growth-period models, they explored growth patterns and light distribution within 3D canopies, achieving satisfactory results. Burgess et al. [?] reconstructed 3D intercropping population structures of peanut and millet using multi-view vision systems, estimated leaf area index, and explored light environment and photosynthesis conditions in intercropping systems, directly guiding optimized field planting. The most direct application of field crop 3D reconstruction is acquiring canopy-level phenotypes to investigate crop growth patterns and population structures, making it an important technical tool for precision agriculture. summarizes research on 3D reconstruction of different field crop populations.

The application status of 3D reconstruction technology in field populations is similar to that in single plants. Before 2010, rule-based methods were predominantly used due to low cost and high speed, though with low precision. When higher precision is required, binocular or multi-view imaging systems are more commonly used. In recent years, faster sampling and reconstruction methods (depth cameras, lidar, 3D scanners) have been widely adopted. These instruments are more convenient and simpler to use, with precision generally meeting requirements (though not as high as image-based methods), but they are often expensive and time-consuming. The 3D population models established through these methods can rapidly acquire a series of canopy phenotypes such as plant height, canopy width, and leaf area index through computer programs [?], thereby accelerating field variety breeding and crop growth diagnosis.

The main challenge in current field population 3D reconstruction research is the significant noise in initial reconstruction results. How to separate target crop populations from complex initial reconstructions through integration of computer vision, deep learning technology, and various algorithmic tools remains a current research focus and difficulty.

3.3 Crop Root System 3D Reconstruction

Non-destructive and accurate observation of crop root growth has long been a desired approach for many plant scientists, and 3D reconstruction technology makes this possible. Metzner et al. [?] used MRI and CT to perform 3D reconstruction of root systems in soil media, which is significant for non-destructive dynamic observation of roots in soil and enables root research independent of special media. Livingston et al. [?] conducted more detailed and microscopic root research, using microscopes and optical imaging systems to perform 3D reconstruction of soybean root nodules, solving problems of vascular bundle continuity or termination that cannot be described by 2D images. Clearly, crop root system 3D reconstruction is an important tool for studying root architecture and provides a crucial foundation for further research on root nodule distribution patterns.

Root system 3D reconstruction represents a major challenge in crop 3D reconstruction research. This paper compiles recent research on crop root system 3D reconstruction, detailed in .

As shown in , root reconstruction in transparent media generally uses 3D scanners or multi-view vision technology, while root reconstruction in soil media employs CT or MRI acquisition combined with software algorithms. Soil media root reconstruction is the ultimate goal and a current research hotspot. The main difficulty lies in data acquisition, as expensive large equipment such as CT or MRI is currently required, resulting in high initial research costs. However, with the popularization of CT and MRI equipment, usage costs have substantially decreased. Additionally, 3D model construction algorithms based on MRI and CT data are relatively mature, with integrated software such as WinRhizo already available. As technology advances, further reductions in sampling equipment and costs will greatly promote root system 3D reconstruction technology development, providing important support for biologists to better study root morphology, physiology, and biological characteristics.

Currently, two main problems exist in crop root system 3D reconstruction research: first, basic image denoising before algorithmic 3D model generation cannot be automated; second, sampling equipment is expensive. These two issues represent major obstacles to current research on 3D root system reconstruction in soil media.

4 Prospects

4.1 Full Automation of the Crop 3D Reconstruction Workflow Will Be a Key Factor Constraining Technology Popularization

Whether for single plants, field populations, or root systems, the overall workflow of crop 3D reconstruction technology is consistent, including sampling, denoising, model generation, segmentation, and phenotypic extraction. This complex and comprehensive process requires relatively professional researchers, and to date, no fully automated system has emerged, resulting in low reconstruction throughput that cannot meet the demands of large-scale phenotyping projects and thereby affecting technology popularization. The key to overcoming this technical barrier is developing computer software systems that integrate with sampling systems to achieve automatic denoising, automatic model generation, automatic segmentation, and automatic phenotypic measurement. Although numerous attempts have been made [?], full workflow automation remains distant.

In 2016, Donné et al. [?] from Ghent University designed and developed a hardware-software integrated system for maize single-plant 3D reconstruction and phenotyping called PhenoVision, which attempted automated plant 3D reconstruction workflows and achieved automatic acquisition of plant length, width, height, and projected area. However, it could not measure finer phenotypes such as leaf area and leaf angle, and performed poorly for more complex plants like soybean. Additionally, companies have invested in developing 3D plant generation systems, such as Trait4D [?], which automates the process from reconstruction to phenotyping for potted crops and can extract multiple phenotypes including plant height and canopy width. However, it remains incapable of handling fine-scale phenotypes (leaf area, node number, internode spacing) and complex plants (those with high canopy coverage). Currently, these problems focus on algorithm design and development for complex plant reconstruction and 3D plant segmentation, which will remain hot topics in crop 3D reconstruction research for the foreseeable future.

4.2 Crop 3D Model Reconstruction Will Become the Basic Unit Constituting Crop 4D Phenotypes

We are currently in the information age where information carriers have surpassed traditional data entry modes. From the perspective of machine vision technology, crop phenotypes can be reclassified based on phenotype description carriers into four categories. The first category is 1D phenotypes, which describe specific measurement metrics of crops such as plant height, canopy height, leaf area, and grain length and width—representing the primary means of traditional crop trait description. The second category is 2D phenotypes, which are comprehensive phenotypes recorded through photographs. Due to limitations of 2D images, descriptions are incomplete; for example, top-view photos can describe leaf color and record flowers and fruits at the canopy top but cannot describe lower canopy conditions. The third category, 3D phenotypes, refers to crop 3D reconstruction models that serve as comprehensive carriers describing complete plant morphological information. A single plant 3D model carries multiple 1D phenotypes while compensating for the limitations of 2D phenotypes, representing one of the most important approaches for describing crop phenotypes. In 2015, Apelt et al. [?] developed the Phytotyping4D system, first using the concept of 4D information carriers to describe spatiotemporal information during crop growth and development. Model sequences composed of crop 3D models at different growth stages along a timeline can be termed crop 4D phenotypes.

Currently, most crop phenomics research still targets 1D phenotypes. However, with the vigorous development of computer vision and artificial intelligence technologies, research and tools related to 2D and 3D phenotypes are gradually increasing, providing important technical support and data foundations for implementing 4D phenotyping research. 4D phenotypes carrying spatiotemporal information throughout the entire crop growth period will become the future target of crop phenomics research and an important focus for breeders.

4.3 Massive Crop 3D Models Will Provide Important Data Foundations for Crop Growth Simulation and Virtual Breeding

Crop growth simulation dynamically and quantitatively describes crop growth, development, and yield formation processes, as well as responses to environmental conditions [?]. Traditional crop growth simulation models can be generally divided into two categories: rule-based crop growth visualization models such as L-systems [?], and quantitative simulation based on growth models, with early research dating back to 1965 when De Wit [?] in the Netherlands studied photosynthetic rates in maize canopies using computer simulation. The common feature of these two approaches is their reliance on rules or models to solve problems—that is, model-driven approaches that require correct or essentially correct models or rules as prerequisites. However, crop growth occurs under complex environmental conditions and diverse genetic backgrounds, making it difficult for most models or rules to achieve universal applicability.

The advent of big data and artificial intelligence technologies provides new approaches for problem-solving. Rapid development in computer technology, sensor technology, and computer vision provides important technical guarantees for 3D reconstruction of various crops under different environmental conditions in agriculture. As crop 3D models increase in number and reconstruction accuracy continuously improves, data-driven crop growth simulation technology will emerge, thereby promoting rapid development of big data-driven crop virtual breeding technology.

4.4 Crop 3D Reconstruction Technology Will Become One of the Important Driving Forces for Rapid Smart Agriculture Development

Smart agriculture is a new production mode that deeply integrates information carriers with agricultural problems through IoT, big data, and artificial intelligence technologies to achieve intelligent decision-making and control in agriculture, representing the advanced stage of agricultural development from digitalization to networking and then to intelligence [?]. The core issues in crop research are breeding and cultivation. To achieve efficient breeding and rational cultivation under smart agriculture concepts and technologies, Sun Kai [?] performed 3D reconstruction of soybean plants using multi-view stereo vision, quantified multiple canopy-level phenotypes, optimized soybean planting density, and realized the complete process from virtual plants to optimized planting density inversion, providing important information for intelligent management and decision-making. Bietresato et al. [?] achieved full growth period monitoring of field crops using lidar-based 3D vision systems, automatically measuring multiple canopy indicators including plant height, canopy width, and leaf area index, compensating for incomplete feedback from 2D image-based visual technology and enabling more accurate and reliable field diagnostics for smart decision-making. Furthermore, large amounts of phenotypic indicators extracted from 3D reconstructions provide high-accuracy and high-throughput phenotypic information for molecular mechanism studies, with further association analysis and genetic mapping becoming important foundations for molecular breeding and smart breeding.

Currently, crop 3D reconstruction technology has been integrated into various aspects of crop science research, playing increasingly important roles in both breeding and cultivation. With further development of modern computer technology, 3D vision technology, and artificial intelligence algorithms, technical bottlenecks in crop 3D reconstruction will be overcome, providing increasingly important information for smart breeding and intelligent cultivation and becoming a crucial driving force for smart agriculture development.

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