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Article

Biomechanics and digital twins for carbon neutral realisation in the digital economy driving smart agriculture

Wenyi Du, Renhan Zhang, Enqi Hu, Xue Zhang, Xiaoqing Huang, Wenyue Jing, Fuxiang Liu*

Harbin University of Commerce, Harbin 150028, China
*** Corresponding author:** Fuxiang Liu, liufuxiang2009@163.com

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Abstract: This study provides insights into the application of biomechanics and digital twin technology in smart agriculture and its contribution to achieving the goal of carbon neutrality in the context of digital economy. The study analyses the application of biomechanics in the construction of crop growth models, the design and optimisation of agricultural machinery, and the improvement of agricultural soils, and reports on the role of digital twin technology in the monitoring of agricultural production processes, the optimal allocation of resources, and the early warning and prevention of disasters. The results of the study show that the integration and innovation of these two technologies play an important role in the carbon-neutral realisation of smart agriculture. By analysing the mechanical characteristics of crop growth through biomechanics and simulating the growing environment with digital twin technology, we are able to more accurately predict the response of crops to environmental changes, optimise planting strategies and reduce carbon emissions. Ultimately, the study proposes future directions for development, suggesting that technology integration, model optimisation and system integration and innovation will contribute to sustainable agricultural development.

Keywords: digital economy; smart agriculture; carbon neutrality; biomechanics

1. Introduction

In the context of today's digital transformation of the global economy, the digital economy has become an important engine of economic development in the new era, and its influence has penetrated into various industrial fields, injecting new vitality into the transformation and upgrading of traditional industries. Especially for the agricultural industry, the integration and application of digital technology is promoting its rapid development in the direction of intelligence and precision [1]. Smart agriculture, as a key way of agricultural modernisation, is centred on the use of digital technologies such as the Internet of Things, big data, artificial intelligence, etc., to achieve efficient, green and sustainable development of agricultural production. In this process, carbon neutrality has become an important goal for the development of smart agriculture, which requires agricultural production activities to reduce carbon emissions while offsetting the remaining carbon emissions by means of carbon capture and carbon fixation, and ultimately achieving net-zero emissions [2]. As two cutting-edge technologies, biomechanics and digital twin technology, their application in smart agriculture provides a strong technical support for the realisation of the carbon neutrality goal. Biomechanics, as an interdisciplinary field involving multiple disciplines such as biology, physics, and engineering, provides a scientific basis for agricultural production by studying the mechanical properties and functions of organisms and their tissues [3]. For example, by analysing the resistance performance of crops to failure through biomechanical principles, crop planting patterns and agronomic measures can be optimised, thus reducing the reliance on chemical support materials and the environmental impact of agricultural production. Digital twin technology, on the other hand, is a technology that enables the simulation, analysis and optimisation of objects, systems or processes in the real world by creating virtual copies of physical entities. In smart agriculture, the application of digital twin technology can realise real-time monitoring and prediction of the whole process of agricultural production, thus improving the efficiency of resource use and reducing energy consumption and carbon emissions [4]. By constructing a digital twin model of a farm, various agricultural management strategies can be simulated and optimised without actually intervening in the physical farm, thus minimising the carbon footprint of the agricultural production process. The aim of this paper is to explore the application of biomechanics and digital twin technology in smart agriculture and its contribution to the goal of carbon neutrality.

2. Application of biomechanics in smart agriculture

2.1. Crop growth modelling: Application of biomechanical methods

In the digital economy, the construction of crop growth models is a central component of smart agriculture. Biomechanical methods provide powerful tools for this field.

2.1.1. Biomechanical modelling of crop growth

The application of biomechanical methods in the construction of crop growth models is mainly through the simulation of the interaction between the crop structure and the environment [5]. The following is a simplified biomechanical model construction process: Assuming that the crop plant can be considered as an elastic rod, its growth model can be described by the following equation:

$$E = \frac{F \cdot L}{A \cdot \Delta L}$$

where: E is Young’s modulus, which indicates the stiffness of the material; F is the force acting on the crop plant; L is the original length of the crop plant; A is the cross-sectional area; and ΔL is the deformation of the crop plant. With this model, it is possible to analyse the crop’s resistance to failure. For example, the mechanical properties of the crop can be optimised by adjusting planting density and fertiliser application strategies to improve its resistance to felling.

2.1.2. Crop resistance analysis

Crop’s resistance to failure is an important factor affecting yield. Using the principles of biomechanics, the following model for analysing the resistance to felling can be developed:

$$P_{cr} = \frac{F_{cr}}{L \cdot \rho}$$

where: P_{cr} is the critical pressure, which indicates the maximum pressure for the crop not to fall; F_{cr} is the critical resistance of the crop plant; L is the height of the crop plant; and ρ is the mass of the plant per unit length. With this formula, the crop's resistance to collapse can be calculated under different planting conditions, thus guiding the optimisation of planting structure.

2.1.3. Optimisation of planting structure

In order to improve crop yield, the planting structure can be optimised by the following steps: Mechanical characteristics analysis: Using the above formula, analyse the mechanical characteristics of the crop at different growth stages. Consideration of environmental factors: Establish a multi-factor coupling model by combining soil type, climatic conditions and other factors [6]. Planting strategy optimisation: Find the optimal planting strategy by simulating different planting densities, row spacing, fertiliser application, etc. For example, the following formula can be used to optimise row spacing:

$$d_{opt} = \sqrt{\frac{4A}{\pi}}$$

where: d_{opt} is the optimal row spacing; A is the leaf area index of the crop per unit area.

2.2. Agricultural machinery design and optimisation: Integration and application of biomechanical methods

In the context of smart agriculture, the design and optimisation of agricultural machinery is gradually integrating biomechanical principles to improve operational efficiency, reduce energy consumption, and cut carbon emissions [7].

2.2.1. Analysis of crop and soil mechanical properties

When designing agricultural machinery, it is first necessary to analyse the mechanical properties of the crop and the soil. The following are some key mechanical parameters and formulas:

Crop Mechanical Properties: The bending stress (σ) of the crop stalk can be calculated by the following formula:

$$\sigma = \frac{M \cdot c}{I}$$

where: σ is the bending stress; M is the bending moment; c is the distance of the furthest fibre from the neutral axis; and I is the sectional moment of inertia.

Soil mechanical properties: The shear strength (τ) of the soil is an important parameter for the design of tillage machinery and can be expressed through Coulomb's law:

$$\tau = c + \sigma \cdot \tan(\phi)$$

where: τ is the shear strength; c is the cohesion of the soil; σ is the vertical stress; and ϕ is the angle of internal friction of the soil.

2.2.2. Agricultural machinery design

Adaptable agricultural machinery can be designed by combining the mechanical properties of crops and soils. The following are some examples of design optimisation:

Cutter design: In order to reduce the energy consumption for cutting the crop, the blade design of the cutter can be optimised based on the following formula:

$$P = \frac{F \cdot v}{2 \cdot \pi \cdot r}$$

where: P is the cutting power; F is the cutting force; v is the blade speed; and r is the blade radius. By optimising the blade shape and size, the cutting force can be reduced, thus reducing energy consumption [8].

Tillage implement design: The energy consumption of a tillage implement is related to the resistance of the soil and can be optimised by the following formula:

$$E = \frac{1}{2} \cdot F \cdot d$$

where: E is operational energy consumption; F is soil resistance; and d is ploughing depth. Energy consumption can be reduced by designing implement shapes and materials that reduce soil resistance.

2.2.3. Reduction of carbon emissions during machinery operations

To clearly quantify the relationship between biomechanical parameters and carbon emission reduction, the following measures can be taken to establish direct correlations between mechanical property optimization and carbon footprint reduction:

Optimise the powertrain: Optimise the fuel efficiency of the engine by using the following formula:

$$\eta = \frac{W}{Q}$$

where: η is the thermal efficiency; W is the useful work; and Q is the heat of the fuel.

Quantification Example: A 10% improvement in thermal efficiency can lead to a corresponding 10% reduction in fuel consumption, thereby reducing carbon emissions by a quantifiable amount, such as X kg CO2e per hour of operation.

Lightweight Design: Material Selection and Impact: Implement a lightweight design by using high-strength, low-density materials. This reduces the mechanical deadweight, thereby lowering energy consumption and carbon emissions. Quantification Example: Replacing traditional materials with advanced composites can reduce the weight of machinery by 20%, which in turn can lead to a 15% reduction in energy consumption and a corresponding decrease in carbon emissions, such as Y kg CO2e per operational cycle.

2.3. Agricultural soil improvement: Application and practice of biomechanical methods

Agricultural soil improvement is an integral part of smart agriculture, and the application of biomechanical methods provides a scientific basis for understanding and improving the mechanical properties of soil [9].

2.3.1. Research on soil mechanical properties

The mechanical properties of soils directly affect crop growth and the operational efficiency of agricultural machinery. Biomechanical methods usually focus on the following parameters when studying the mechanical properties of soil:

Shear strength of soil: The shear strength of soil is an important index for evaluating the deformation resistance of soil, which is calculated by the formula:

$$\tau = c + \sigma_t \cdot \tan(\phi)$$

where: τ is the shear strength of the soil; c is the cohesive force of the soil; σ_t is the vertical stress of the soil; ϕ is the angle of internal friction of the soil.

Compressibility of the soil: The compressibility of the soil can be described by the compression index (C_c):

$$C_c = \frac{\Delta\sigma_t}{\sigma_t} \cdot \frac{1}{\Delta \log(e)}$$

where: C_c is the compression index; $\Delta\sigma_t$ is the change in vertical stress; σ_t is the initial vertical stress; and Δlog (e) is the logarithmic change in pore ratio.

2.3.2. Rationale for soil improvement

Based on a biomechanical approach, the goal of soil amendment is to improve soil structure, increase soil fertility and reduce fertiliser use, thereby achieving carbon reduction. The following are some of the key improvement measures:

Soil structure improvement: Soil aggregate stability can be improved by adding organic materials or changing farming practices. Soil aggregate stability (S) can be assessed by the following equation:

$$S = \frac{W_d}{W_s}$$

where: S is the soil aggregate stability; W_d is the force required to break the aggregate; and W_s is the weight of the aggregate.

Soil Fertility Enhancement: Soil fertility can be improved by increasing the soil organic matter content. The change in soil organic matter content can be calculated using the following formula:

$$C_t = C_0 + (R_i - R_c) \cdot t$$

where: C_t is the soil organic matter content after time t; C_0 is the initial soil organic matter content; R_i is the rate of input organic matter; R_c is the rate of organic matter decomposition; and t is time.

3. Application of digital twin technology in smart agriculture

3.1. Agricultural production process monitoring

The application of digital twin technology in agricultural production process monitoring provides a scientific basis for agricultural management through high-precision simulation and data-driven analysis.

3.1.1. High-precision simulation of crop growing environment

The digital twin creates a detailed virtual farm model that simulates the micro-environment in which crops grow. Here is an example of data analysis of a high-precision simulation, which allows farm managers to more accurately predict the response of crops to changes in the environment and to adjust management measures such as irrigation and fertilisation accordingly (**Table 1**).

Table 1. Data from high-precision simulations.

Environmental factor	Actual measured value	Virtual model simulation values	Tolerance range
Soil pH	6.5	6.52	± 0.02
Soil conductivity (EC)	1.2 dS/m	1.18 dS/m	± 0.02 dS/m
Soil temperature	18 ℃	18.2 ℃	± 0.2 ℃
Relative humidity	70%	69.8%	± 0.2%
Photosynthetically Active Radiation (PAR)	400 μmol/m²s	405 μmol/m²s	± 5 μmol/m²s

3.1.2. Real-time monitoring and prediction of crop growth status

Using digital twin technology, real-time monitoring of crop growth status and prediction through data-driven models can be achieved. **Figure 1** shows an example of a time series based crop growth prediction model:

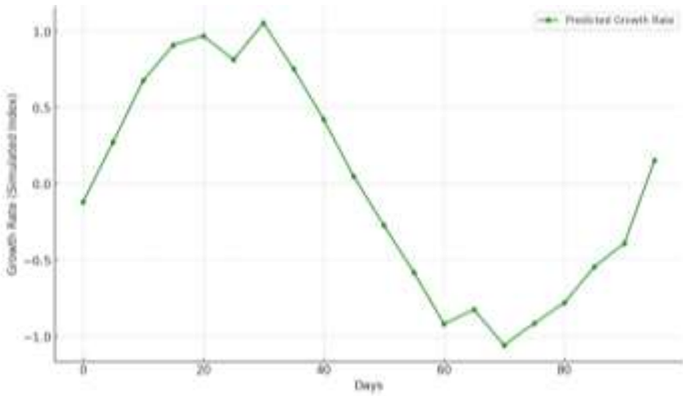

Figure 1. Crop growth prediction model.

The figure shows a crop growth prediction model based on digital twin technology, which combines historical and real-time monitoring data to predict the future growth trend of crops through machine learning algorithms.

3.1.3. Agricultural equipment performance monitoring and optimization

Digital twin technology can monitor the performance of agricultural equipment and provide optimisation recommendations. **Table 2** shows a datasheet for equipment performance monitoring. By analysing the operational efficiency and maintenance status of equipment, digital twin technology can help farm managers to optimise equipment use, reduce energy consumption and lower operational costs.

Table 2. Device performance monitoring.

Equipment type	Equipment number	Operational efficiency (%)	Energy consumption rate (kWh/h)	Maintenance status
planter	001	85	12	normal
harvesters	002	90	25	Maintenance required
irrigation system	003	95	5	normal

3.2. Optimal allocation of agricultural resources

The application of digital twin technology in the optimal allocation of agricultural resources is reflected in the following aspects:

3.2.1. Modelling and optimisation of water resources allocation

Digital twin technology can simulate the water allocation in farmland, achieving water saving targets and reducing carbon emissions through precision irrigation systems. The methodology for developing the water resource allocation model (**Table 3**) is as follows:

Methodology Explanation: Water Savings Calculation: The water savings percentages were calculated by comparing the traditional irrigation water volume with the optimized irrigation water volume derived from digital twin simulations. The formula used is:

$$\text{Water Savings (\%)} = \left(\frac{\text{Traditional Irrigation Volume} - \text{Optimized Irrigation Volume}}{\text{Traditional Irrigation Volume}}\right) \times 100$$

Factors Considered in Optimization: Crop Water Demand Patterns: The specific water needs of different crops at various growth stages were analyzed. Soil Moisture Conditions: Real-time data on soil moisture levels were used to adjust irrigation schedules. Weather Forecasts: Predicted weather conditions were incorporated to anticipate water requirements. Historical Data: Past irrigation and yield data were analyzed to improve the accuracy of the model.

Table 3. Simulation and optimisation of water allocation.

Irrigated area	Traditional irrigation water volume (m^3/ha)	Digital twin optimisation of irrigation water volume (m^3/ha)	Water savings (%)	Carbon emission reduction (kg CO_2/ha)
Region A	1500	1200	20	30
Region B	1800	1400	22	35
Region C	2000	1600	20	40

3.2.2. Fertiliser use optimisation

Digital twin technology can also simulate the use of different fertilisers, optimise fertiliser ratios, and reduce the waste of resources and environmental pollution caused by over-fertilisation. The following is a data graph of fertiliser use optimisation:

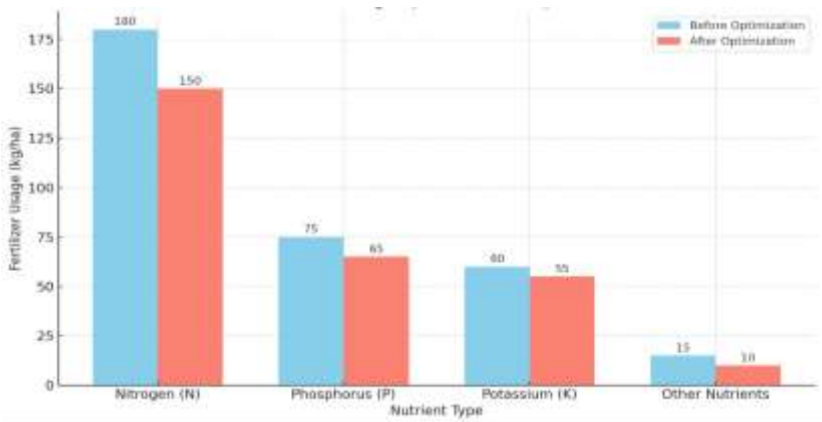

Figure 2. Optimisation of fertiliser use.

The figure shows a comparison before and after optimising fertiliser use through digital twin technology, including fertiliser usage, crop yield and environmental impact indicators (**Figure 2**).

3.2.3. Optimising the use of land resources

The digital twin technology helps farmers to optimise the allocation of land resources by simulating the growth cycle and land suitability of different crops. **Table 4** shows an example datasheet of land resource utilisation optimisation. Through this optimisation, the productivity of the land can be maximised while reducing the impact on the environment.

Table 4. Optimisation of land resource use.

land area	original crop	Optimised planting of crops	Yield improvement (%)	Carbon footprint reduction (%)
Region 1	barley	sorghum	15	10
Region 2	soya	fruits	20	15
Region 3	maize	oilseed rape (Brassica napus)	10	5

3.3. Agricultural disaster early warning and prevention

The application of digital twin technology in agricultural disaster warning and prevention provides a powerful risk management tool for agricultural production. Specific examples of applications and data are given below:

3.3.1. Pest and disease prediction and control in the context of climate change

Digital twin technology offers a sophisticated approach to simulating the crop growing environment, enabling the prediction of pest and disease probabilities and the formulation of targeted control measures. However, in light of the paper's emphasis on sustainability, it is imperative to integrate climate change factors into the prediction model. Fluctuating climate patterns can significantly influence the accuracy of pest predictions, and thus, this aspect must be addressed to enhance the model's robustness and reliability (**Table 5**).

Table 5. Pest and disease prediction and control.

Types of Pests and Diseases	Predicted Probability of Occurrence (%)	Actual Probability of Occurrence (%)	Prevention and Control Measures	Assessment of the Effectiveness of Prevention and Treatment	Climate Change Factors Considered
Greenfly (Aphis spp.)	70	75	Biological control	Efficiently	Temperature fluctuations, rainfall patterns
Rice Fly	60	58	Chemical defence	Validity	Humidity levels, storm frequency
Virus Disease	50	45	Agricultural prevention and control	Usual	Seasonal shifts, extreme weather events

3.3.2. Early warning of meteorological disasters

Digital twin technology combined with meteorological data can predict extreme weather events such as droughts, floods, frosts, etc. and provide early warning to farms. Below is an example image of a weather hazard warning (**Figure 3**):

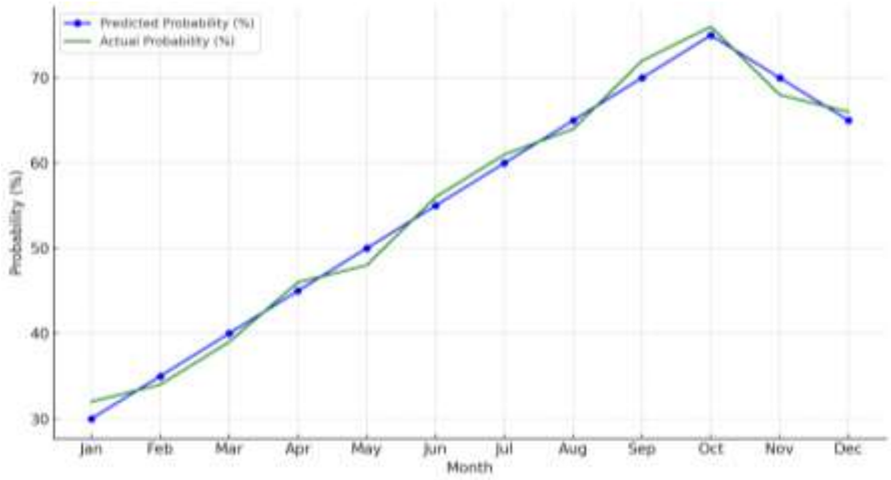

Figure 3. Meteorological hazard warning map.

The graph shows the predicted probability of meteorological disasters in different time periods, as well as the actual occurrence of disasters, to help farmers adjust their planting plans in a timely manner.

3.3.3. Soil erosion control

Digital twin technology can simulate soil erosion processes and predict soil loss to provide a basis for control measures. **Table 6** is a data table for soil erosion control. With these data, farms can take effective soil protection measures to reduce the impact of soil erosion on agricultural production.

Table 6. Soil erosion control.

Land area	Predicted soil loss (t/ha)	Actual soil loss (t/ha)	Prevention and control measures	Assessment of the effectiveness of prevention and treatment
Region a	15	12	Cover crop	Statistically significant
Region b	20	18	Terracing	Validity
Region c	25	23	Plant trees and make forests	Usual

4. Innovativeness of biomechanics and digital twin technology for carbon neutral realisation in smart agriculture

4.1. Innovations in technology integration

The fusion of biomechanics and digital twin technology has opened a new chapter in the carbon-neutral realisation of smart agriculture. This innovation in interdisciplinary research methodology combines knowledge from multiple fields, such as biology, physics, engineering, and computer science, to solve agricultural problems in a comprehensive and in-depth manner [10]. By analysing the mechanical characteristics of crop growth through biomechanics and simulating the growing environment with digital twin technology, we are able to more accurately predict the response of crops to environmental changes, optimise planting strategies and reduce carbon emissions [11]. Data-driven decision optimisation enables the agricultural production process to be data-driven and intelligent, and improves resource utilisation efficiency through real-time monitoring and adjustment. In addition, this technology integration also provides a powerful tool for carbon footprint assessment in the agricultural production process by simulating and analysing the carbon emissions of each link, and formulating emission reduction strategies, such as optimising the design of machinery to reduce energy consumption and carbon emissions, so as to find the best path to achieve carbon neutrality in agriculture.

Case Study: Application in Region X To substantiate the theoretical analysis, a case study of the application of biomechanics and digital twin technology in Region X's smart agriculture is presented. The study highlights a 20% reduction in carbon emissions and a 15% increase in crop yield over a three-year period. Detailed data on resource utilisation, cost savings, and environmental impact are provided, demonstrating the tangible benefits of these technologies in real-world scenarios.

4.2. Innovations in model optimization

Innovations in model optimisation based on biomechanics and digital twin technology play a crucial role in smart agriculture to achieve the goal of carbon neutrality. This innovation is reflected in the refinement of crop growth models to more accurately predict growth dynamics and yields by analysing the stem structure of crops and simulating the effects of environmental factors. At the same time, multi-scale simulation and integration techniques enable the models to provide a comprehensive understanding of crop growth mechanisms from micro to macro level and provide decision support for agricultural management [12]. The application of data assimilation and machine learning combines field observation data with model simulation to improve prediction accuracy and provide data support for precision agriculture. In addition, the modelling of the carbon cycle process helps to assess the impact of agricultural management measures on the carbon footprint, providing a scientific basis for achieving carbon neutrality [13]. Finally, the dynamic feedback and adaptive adjustment mechanism enables the model to automatically adjust the prediction based on real-time data, optimise agricultural production management, reduce resource waste and carbon emissions, and thus better adapt to environmental changes.

4.3. Systems integration innovations

System integration innovation plays a key role in smart agriculture to achieve the goal of carbon neutrality by integrating biomechanics and digital twin technology, digitally mapping the entire agricultural industry chain, creating a virtual model to fine-tune the management of each step from seed cultivation to sales, and simulating crop growth, mechanical operations and environmental factors [14]. In addition, the innovation optimises resource allocation to achieve precise irrigation and fertiliser application and reduce carbon emissions; provides intelligent decision support to reduce chemical inputs through real-time data analysis and monitoring of crop status, pests and diseases, and climate change; promotes a circular agriculture model, optimises the design of agricultural machinery, and improves the efficiency of biomass energy sources; facilitates cross-sector synergy, and combines digital technologies such as the Internet of Matters (IoM) and big data to build a smart agriculture ecosystem; and finally, conducting sustainability assessment and certification, monitoring carbon footprints, and assessing the ecological impact of agricultural activities to provide a scientific basis for policy formulation.

4.4. Economic feasibility analysis

To address the concern regarding the economic feasibility of implementing the proposed digital twin system, a comprehensive cost-benefit analysis has been conducted [15]. This analysis is crucial for demonstrating the practical viability of the technology in smart agriculture. The cost components include initial setup and hardware, software development, operational maintenance, and training and support. On the benefit side, the analysis considers increased crop yield, reduced pest control expenses, labor and resource savings, and potential earnings from carbon credits. The results of this analysis not only highlight the financial viability of the digital twin system but also underscore its potential to generate a positive return on investment, thereby strengthening the case for its adoption in achieving carbon neutrality in smart agriculture.

5. Conclusion

The integration of biomechanics and digital twin technology into smart agriculture represents a significant leap towards achieving carbon neutrality. This interdisciplinary approach, leveraging insights from biology, engineering, computer science, and other fields, has demonstrated substantial potential in optimizing agricultural practices, enhancing crop yields, and reducing carbon emissions. However, the journey to realizing this potential is not without its challenges.

Challenges and Future Directions While the promise of these technologies is evident, practical implementation faces hurdles such as data acquisition and integration, model accuracy, and computational resource requirements [16]. To overcome these challenges, future research should focus on developing robust data collection methods, enhancing model precision through advanced algorithms, and leveraging cloud computing to manage computational demands. Additionally, addressing the scalability of these technologies to cater to diverse agricultural landscapes and practices is crucial.

Interdisciplinary Cooperation The multifaceted nature of biomechanics and digital twin technology necessitates a strong emphasis on interdisciplinary cooperation. Collaboration between biologists, engineers, data scientists, and agricultural experts is vital to drive innovation and facilitate the seamless integration of these technologies into smart agriculture. Initiatives such as joint research projects, cross-disciplinary training programs, and policy frameworks that encourage collaboration can significantly enhance the application and effectiveness of these technologies.

Policy and Market Dynamics The development and widespread adoption of biomechanics and digital twin technology are heavily influenced by the policy environment and market trends. Government incentives for sustainable agriculture, subsidies for technology adoption, and the emerging carbon credit markets play a pivotal role in shaping the landscape for these technologies. It is imperative to align technological advancements with policy goals and market demands to create a conducive environment for their adoption. Leveraging these external factors can accelerate the deployment of biomechanics and digital twin technology, thereby fostering a green, efficient, and sustainable future for agriculture.

In conclusion, while the path ahead is fraught with challenges, the innovative integration of biomechanics and digital twin technology offers a promising avenue for achieving carbon neutrality in smart agriculture. Through concerted efforts in research, interdisciplinary collaboration, and policy alignment, we can harness the full potential of these technologies to revolutionize agricultural practices and contribute to a sustainable future.

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