

Article

The construction of a smallholder credit evaluation system based on biomechanical characteristics: A synergistic analysis of crop growth potential and risk management

Annan Li, Zhen Cao, Na Fu*

Tianjin Agricultural University, Tianjin 300392, China

* Corresponding author: Na Fu, scarlett_fn@126.com

CITATION

Li A, Cao Z, Fu N. The construction of a smallholder credit evaluation system based on biomechanical characteristics: A synergistic analysis of crop growth potential and risk management. *Molecular & Cellular Biomechanics*. 2025; 22(4): 908. <https://doi.org/10.62617/mcb908>

ARTICLE INFO

Received: 25 November 2024

Accepted: 18 February 2025

Available online: 5 March 2025

COPYRIGHT

Copyright © 2025 by author(s).
Molecular & Cellular Biomechanics
is published by Sin-Chn Scientific
Press Pte. Ltd. This work is licensed
under the Creative Commons
Attribution (CC BY) license.
<https://creativecommons.org/licenses/by/4.0/>

Abstract: This study proposes an innovative credit evaluation system for small-scale farmers by integrating biomechanical characteristics analysis with traditional credit assessment methods. Through the Analytic Hierarchy Process (AHP), we develop a comprehensive evaluation framework encompassing five dimensions: farmers' personal characteristics, solvency, credit status, loan guarantee, and production operations. The research introduces a novel biomechanics-driven credit risk assessment model (BICAM) that establishes quantitative relationships between plant mechanical properties and agricultural management risks. The study particularly focuses on three key biomechanical indicators: root system extension force, stem supporting strength, and leaf-environment interaction, which provide objective measures of farmers' technical capabilities and risk management potential. The integration of these biomechanical parameters has significantly improved credit risk prediction accuracy, with the Area Under the Curve (AUC) showing a 16% improvement compared to traditional evaluation methods. A multi-scale modeling approach combining fractal-mechanical coupling for root systems, beam theory for stem dynamics, and mechanical-physiological coupling for leaves provides a robust theoretical foundation. The findings suggest that farmers demonstrating superior understanding and management of crop biomechanical properties typically exhibit better credit reliability and operational stability, offering financial institutions new insights for agricultural lending risk assessment while promoting more scientific approaches to agricultural risk management.

Keywords: crop growth potential; biomechanical modeling; plant mechanical properties; small-scale farmers; credit evaluation system; analytic hierarchy process (AHP); biomechanical principles

1. Foreword

In the context of globalization and market economy, agriculture as the basic sector of national economy, its stability and development are of great significance to ensure national food security, promoting farmers' income and promoting rural economic and social development, but the effective financial support is the key factor to promote agricultural development [1]. At present, small farmers are still the largest number of agricultural operators in China. According to the third national agricultural census in 2016, there are about 230 million agricultural operating households in China, among which the number of small farmers accounts for about 98.27%. Therefore, the development of China's agricultural modernization is largely affected by small farmers. However, due to the particularity of agricultural production, small farmers are often faced with a series of challenges, such as capital shortage, information

asymmetry and high market access threshold. These problems have a more serious lending risk for the banks that use lending activities [2].

Inclusion of the crop growth potential analysis based on biomechanical characteristics opens a new dimension in assessing farmers' competence in managing agricultural risk. Conjoint realization of farmers' ability to appraise and manage crop growth through dynamics of the root system, strength of stem support, and interaction between leaf and environment shows value in their technical and operational stability. It further adds to the traditional methods of credit evaluation by considering agricultural management competence as an essential indicator of the creditworthiness of farmers.

In order to solve these problems, it is particularly urgent to construct a scientific and reasonable credit evaluation system for small farmers. The establishment of the credit evaluation system aims to collect and analyze the credit information of small farmers and evaluate their credit status, so as to provide a decision-making basis for financial institutions, reduce credit risks, and improve the accessibility and efficiency of financial services. This will not only help small farmers to obtain the necessary production funds, but also to promote their connection with the market, and enhance the competitiveness of the entire agricultural industry chain. Developing countries have always taken credit as a policy tool. With the deepening of the construction of social credit system and the widespread use of big data in social credit investigation methods, China's personal credit investigation market has a large space for [3]. In the future, with the coverage advantage of the Internet to the long tail group and the advantage of big data for credit investigation, personal credit investigation is expected to achieve leapfrog development. Personal credit investigation agencies are a supplement to the central bank's credit investigation center. According to the data of the seventh 2020 census, there are 1.443 billion people in China, and 46 million people still do not have any credit history. The lack of credit history and collateral makes it difficult for banks to borrow money for [4].

In short, how to finance small farmers, and how to build a safe, efficient and win-win agricultural financial model has become an important problem today. In the process of constructing the financial model, how to build the credit evaluation system of small farmers, reduce the credit risk, and realize the capital "credit loan" has become the most important issue. Therefore, this paper, through the hierarchical analysis method, rates the factors affecting the credit of small farmers, and constructs the credit evaluation system of small farmers, which has important theoretical and practical significance to reduce the risk of agricultural loans, effectively solve the financing of small farmers with low satisfaction rate, high risk and difficult to control. This study breaks through the traditional agricultural credit evaluation paradigm and proposes, for the first time, a biomechanics-driven credit risk assessment model (Biomechanics-informed Credit Assessment Model, BICAM). This model establishes a quantitative relationship between the mechanical performance responses of plant organs (such as root anchorage work, stem modulus of elasticity, and leaf tear resistance strength) and agricultural management risks, providing an objective biophysical basis for evaluating the risk management capacity of farmers.

2. Related literature review

2.1. Definition of small farmers and related studies

Although “small farmers” is widely used once, the academic circle has not given a unified definition of its specific meaning. However, with the convening of the 18th National Congress of the Communist Party of China, small farmers were widely concerned by scholars and studied [5]. Lin, Wang [6] taking 50 mu as the standard, the farmers of less than 50 mu are defined as small farmers. According to Ye and Zhang [7], agricultural lands measuring less than 50 mu within the elastic range can be classified as “small farmers” holdings. This paper holds that “small farmers” usually refers to the agricultural micro subject of family and production and consumption [8]. And the land in the less than 50 mu within the elastic range can be called “small farmers”.

2.2. Related research on the credit evaluation system

First of all, the relationship between credit system construction and economic growth, credit is the inevitable condition of agricultural economic development [9]. Foreign research on credit evaluation is mainly credit consumption and personal credit evaluation [10]. According to Xie, Xiang, and Wang [11], the primary factor contributing to the success of “Lu’s model” is the establishment of a comprehensive rural credit evaluation system. Meanwhile, Li from Baohui [12] argues that the development of the rural credit system provides substantial support and assurance for implementing the rural revitalization strategy. Therefore, it is necessary to comprehensively promote the construction of rural credit system from the three aspects of reshaping the concept of rural credit, ensuring the implementation of rural revitalization strategy, strengthening the responsibility of government credit and improving the modernization of rural governance.

In the course of developing agricultural credit-scoring systems, much focus has been directed toward farmers’ technical skills and risk management capabilities. More recent literature suggests that farmers’ perception about crop growth characteristics and, further, management of agricultural risks acts as an influencing factor in their stability of operation and creditworthiness. The integration of assessment capability of crop growth into the credit evaluation framework is quite recent and might have the capability to enhance the quality and efficiency of risk assessment in agricultural lending. This view puts strong emphasis on the technical skills of farmers and agricultural management capabilities as major indicative factors in the assessment of creditworthiness.

2.3. Related research on peasant household credit evaluation

Farmers’ credit is the expansion of moral standards formed by farmers based on blood and geographical relations. It refers to the ability to obtain goods, services or funds based on the condition of repayment of principal and interest, which is reflected in the organic unity of objective ability and subjective willingness to perform the contract in economic and social life. In the study on farmers’ credit assessment, Chen et al. [13] maintain that the personal credit of Chinese farmers represents a form of

moral social capital, which possesses both the characteristics of production, development, and capital accumulation as well as the qualities of moral norms and constraints. The credit of Chinese farmers is faced with the historic choice of transition from relative credit to contract credit. Secondly, the study on the financial needs of farmers, similar to most developing countries, China's rural financial market also shows a typical duality of formal and informal finance. Chen et al. [14] argue that due to the lack of effective collateral, farmers often face the problems of credit constraints and financial exclusion, so they need to turn to the informal credit with higher interest rates. Regarding strategies for farmer credit evaluation, Cui [15] proposes using machine learning model to evaluate farmers' credit, establishing a model scoring mechanism that provides reference opinions for borrowing for banks and other credit institutions. Additionally, Lai [16] introduces integrated learning method is introduced into the farmer credit risk assessment, and Accuracy, Precision, Recall, F1score to build the farmer credit risk assessment index system, which is conducive to reducing the trust-breaking and default behavior and reducing the non-performing loan ratio of financial institutions.

To sum up, small farmers have financial needs to improve their own production and living conditions, but they have not been paid attention to for a long time, and even have the phenomenon of financial suppression. In the study of peasant household credit evaluation index, scholars mainly focus on the macro level, and put forward rich research results on the construction of rural credit system and credit risk prevention. Although in recent years, some new and more scientific evaluation methods, such as machine learning models and integrated learning methods, have been introduced in the credit evaluation of farmers, most studies do not fully combine the weak characteristics of small farmers and cannot provide help for the subsequent in-depth study of the credit behavior of small farmers. Therefore, this paper hopes to build a scientific and systematic farmer credit evaluation index system, in order to fully understand the behavior logic of farmers 'credit behavior, and deepen the understanding of farmers' credit behavior.

2.4. Advances in agricultural biomechanics research

The application of biomechanics in agriculture has made significant strides, particularly in the realm of precision farming. Biomechanical principles have been integrated into agricultural practices to better understand the mechanical behaviors of plants, thereby optimizing crop management strategies. One of the classic models used in plant biomechanics is the growth model developed by Niklas [17], which describes the relationship between the mechanical forces acting on plant structures and their growth dynamics. This model is particularly useful in understanding how plants respond to environmental stresses, such as wind or drought, and how their mechanical properties can influence overall crop yield and resilience. The role of plant biomechanics in precision agriculture has grown, with new sensors and data analytics methods enhancing our ability to monitor plant health and stress in real time, making it easier for farmers to apply precise interventions when needed.

Furthermore, research has explored the relationship between crop mechanical properties and their resistance to environmental stresses. For instance, studies have

demonstrated how the bending stiffness of stems is closely correlated with lodging resistance, a key factor in determining crop stability under harsh weather conditions. This connection between stem mechanical strength and lodging resistance has profound implications for optimizing crop breeding strategies and improving crop management practices, particularly in areas prone to extreme weather events. By developing crops with stronger stems, farmers can mitigate the risks of crop failure due to lodging, which is one of the leading causes of yield loss in many regions.

The advancement of biomechanical sensor technologies has also led to innovative applications in field monitoring. Recent studies have introduced novel sensors capable of detecting biomechanical properties in situ, offering real-time data on various plant characteristics, including stem strength, root development, and leaf rigidity. According to recent research by Guo [18], these technologies are revolutionizing how farmers track crop health and environmental conditions, providing an unprecedented level of detail that helps in the early identification of crop stressors. These innovations allow farmers to implement timely interventions and make more informed decisions about irrigation, fertilization, and pest control, ultimately improving the efficiency and sustainability of agricultural operations.

Additionally, Decardi-Nelson and You [19] highlight the role of artificial intelligence (AI) in regulating light and climate systems in plant factories. This technology significantly reduces energy consumption and supports sustainable food production. The integration of AI in agriculture, particularly in controlled environments like plant factories, can complement biomechanical research by enhancing crop growth through more precise environmental controls, further aiding farmers in their efforts to optimize yield and minimize risks. By combining mechanical analysis with AI-driven environmental adjustments, farmers can further increase efficiency, sustainability, and resilience in their farming operations.

Incorporating these biomechanical advancements into the broader context of agricultural risk management holds significant promise. By combining mechanical analysis with other data sources such as climate modeling and soil health metrics, farmers can gain a more holistic view of their operations. This integrated approach can enhance decision-making processes, reduce agricultural risks, and improve creditworthiness assessments for smallholder farmers, providing them with better access to financial resources. As agricultural systems become increasingly complex and data-driven, the incorporation of biomechanics into agricultural management frameworks will play a pivotal role in fostering sustainable, resilient farming practices.

3. Biomechanical reconstruction of the credit evaluation system for agricultural management entities

3.1. Construction idea of peasant household credit evaluation index and biomechanical assessment framework

3.1.1. Framework for constructing the peasant household credit evaluation index

Domestic and foreign scholars conduct credit evaluation of farmers in accordance with the classic 5C principle, focusing on character (Character), ability (Capacity),

capital (Capital), mortgage (Collateral) and conditions (cycle situation, Condition) [20]. Some scholars have also analyzed the production behavior and economic behavior of farmers, and constructed the farmer credit evaluation index system from the perspectives of agricultural production process and the characteristics of credit itself. However, the idea of building the peasant household credit evaluation system is mostly conducted to select the international standards or economic principles, many scholars research economic indicators design too much [21], Ignoring the steps that need further optimization, resulting in some indicators reflecting the problem of repeated information, and some have no information on our construction of discriminative prediction models, and even have interference effects. When constructing the index system of farmers' credit evaluation, in addition to economic theories and mature evaluation standards, it is also necessary to select indicators by analyzing the characteristics of farmers' credit behavior in a specific period, and screen and clean up the selected indicators, so as to ensure the scientific and accuracy of the construction of the evaluation index system [22]. At present, there are some problems in the farmer credit system construction, such as repeated construction of departments and insufficient professional operation [23]. Therefore, the construction of the credit evaluation index system of farmers should select the indicators that can not only reflect the solvency or economic status of farmers, but also reflect the repayment willingness of farmers, and the selection of indicators should basically comply with the "5C" evaluation criterion widely recognized by the financial sector.

This paper based on the development of farmers own characteristics and lending behavior characteristics, set up including family characteristics, repayment ability, repayment willingness, stability, macro environment, security situation six affect the farmers credit level, to form a perfect index system can be used for the construction of farmers credit evaluation model, specific indicators see **Table 1**.

Table 1. Primary selection of peasant household credit evaluation index.

Criterion layer (1)	Index layer (2)
Family characteristics	Househead age, gender, head of the household education level, whether in local surname, household ranking son, professional and technical level, health, marital status, migrant city, family members, labor quantity, labor proportion, the elderly, the number of young proportion, the number of family migrant workers, happiness
Repayment willingness	Oto the bank amount, the total amount of borrowing, all total arrears, other channels except the bank lending, family sense of responsibility and the relationship between the neighbors, moral prestige, whether honest and trustworthy, farming by recognition, whether a seat belt according to the lamp, use of credit years, without default record, farmers loan extension or loans
Repayment ability	Fixed assets, peasant household farmland area, current assets, food expenditure, premium expenditure, agricultural expenditure, transfer expenditure, spending income ratio, total expenditure, agricultural productive income, industrial and commercial income, total income, household income, engel coefficient, agricultural income / all income, education training spending ability to obtain information, professional skills training, to attend social group meetings, the frequency and time of the Internet, the degree of new products
Stability	Whether the amount of land changes, the time of living in the local area, the number of years engaged in existing projects, the annual time of agricultural production, the comparison of this year's income and the previous year, and the comparison of income growth and price growth
Environment	Social security in the residence, distance from the city/county center, consumer price index, regional GDP growth rate, agricultural production and operation subsidies, and government subsidies
Security situation	Whether there is guarantee, family security situation, guarantee personnel strength, UNPROFOR team member relationship, UNPROFOR team member strength

3.1.2. Biomechanical assessment framework for agricultural risk management

To enhance the precision and depth of the credit evaluation model, this study introduces biomechanical principles to evaluate the agricultural risk management capabilities of farmers. The integration of biomechanical assessments offers valuable insights into how farmers manage agricultural production and mitigate associated risks. At the core of this framework is the introduction of continuum mechanics theory, which establishes the stress-strain constitutive relationships for plant organs. This theoretical foundation allows for a detailed analysis of how mechanical forces influence plant growth, health, and productivity. Additionally, the biomechanical parameter transfer chain is developed, linking the mechanical properties of plant structures—from the cellular level to tissue strength—ultimately influencing organ functionality and field performance. This approach provides a robust understanding of the dynamic relationships between a plant's mechanical properties and its response to environmental stressors, such as drought or strong winds. By incorporating biomechanical assessments alongside traditional economic indicators, the model offers a more comprehensive evaluation of a farmer's technical proficiency in managing agricultural risks, ultimately leading to a more accurate determination of creditworthiness and operational stability. This holistic approach not only captures the economic status of farmers but also assesses their ability to optimize agricultural practices and adapt to changing conditions, ensuring sustainable productivity and minimizing risk exposure.

3.2. Determination of peasant household credit evaluation index

In order to better avoid the possible default of agricultural business entities (farmers) in the loan process of various situations, it is necessary to build a scientific credit evaluation system. Therefore, the members of the research group first interview with financial institutions to know the data of the agricultural operators they want to know; then interview the agricultural data collected by the Internet of Things; analyze and compare the data, communicate with the relevant experts, and use the hierarchical analysis method (AHP) to build a scientific multi-dimensional and wide-covered farmer credit evaluation system, and solve the problems of incomplete evaluation index and single data source, so as to provide a scientific credit assessment basis for the subsequent model construction [24]. According to the results of the survey, we first divided the peasant household credit evaluation system into five major aspects, including farmers' individual characteristics, farmers' solvency, credit status, loan and guarantee, and production and operation status, and took them as the first-level index. On the basis, the first-level index is subdivided into 16 second-level indicators, as shown in **Figure 1**.

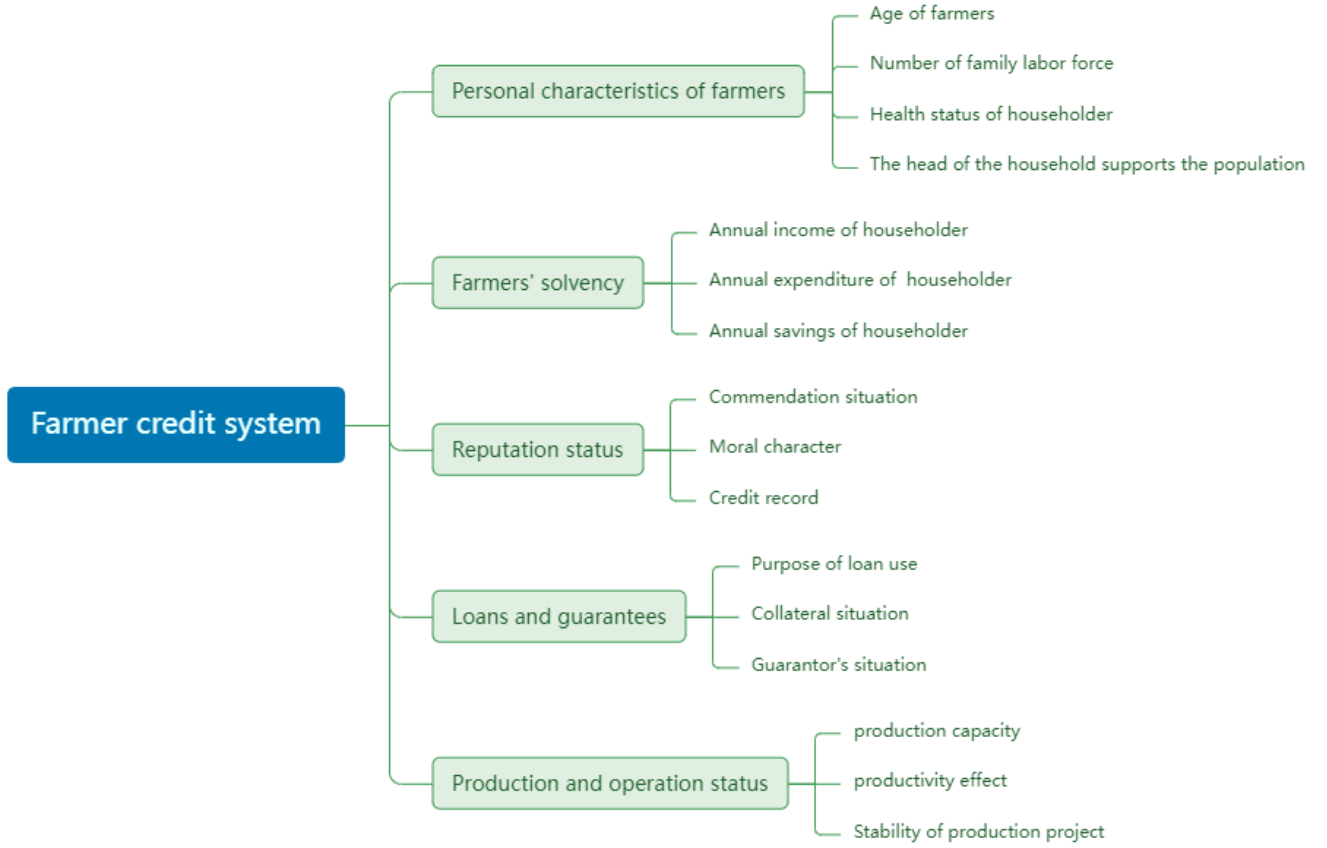


Figure 1. Peasant household credit evaluation index system.

In this paper, the 1–9 scale method is adopted to construct the pairwise judgment matrix. The meanings of the various scales are shown in **Table 1**. Through the judgment and decision of experts in relevant fields based on their work and practical experience, the judgment matrix of each layer of indicators is obtained.

The judgment matrix of the first-level index is shown below.

$$A = \begin{pmatrix} 1 & 1/2 & 3 & 2 & 3 \\ 2 & 1 & 3 & 2 & 4 \\ 1/3 & 1/3 & 1 & 1/3 & 1/2 \\ 1/2 & 1/2 & 3 & 1 & 2 \\ 1/3 & 1/4 & 2 & 1/2 & 1 \end{pmatrix} \quad (1)$$

Similarly, the judgment matrix of the second-level index can be obtained as shown below.

$$B_1 = \begin{pmatrix} 1 & 1/3 & 1/2 & 1/3 \\ 3 & 1 & 2 & 2 \\ 2 & 1/2 & 1 & 1/2 \\ 3 & 1/2 & 2 & 1 \end{pmatrix} \quad (2)$$

$$B_2 = \begin{pmatrix} 1 & 1/2 & 1/2 \\ 2 & 1 & 1/2 \\ 2 & 2 & 1 \end{pmatrix} \quad (3)$$

$$B_3 = \begin{pmatrix} 1 & 1/2 & 1/2 \\ 2 & 1 & 1/2 \\ 2 & 2 & 1 \end{pmatrix} \quad (4)$$

$$B_4 = \begin{pmatrix} 1 & 1/4 & 1/3 \\ 4 & 1 & 2 \\ 3 & 1/2 & 1 \end{pmatrix} \quad (5)$$

$$B_5 = \begin{pmatrix} 1 & 1/2 & 3 \\ 2 & 1 & 4 \\ 1/3 & 1/4 & 1 \end{pmatrix} \quad (6)$$

The index system and data were analyzed using YAAHP10.0 with the following results.

3.2.1. The judgment matrix and calculation results of the primary index—Target layer

First, the hierarchical ranking of the overall level and each factor was conducted, and the results are shown in **Table 2**. In this case, the consistency proportion was $0.0335 < 0.1$, indicating that this matrix passed the consistency test.

Table 2. Single ranking of the overall level and each factor.

Farmers credit system	Individual characteristics of farmers	Household solvency	The status of credibility	Loan and Guarantee	Production and operation status	Wi
Individual characteristics of farmers	1	1/2	3	2	3	0.2641
Household solvency	2	1	3	2	4	0.3715
The status of credibility	1/3	1/3	1	1/3	1/2	0.0782
Loan and Guarantee	1/2	1/2	3	1	2	0.1829
Production and operation status	1/3	1/4	2	1/2	1	0.1033
Consistency check	Maximum eigenvalue: 5.1500, consistency ratio: 0.0335					

3.2.2. Judgment matrix and calculation results of the secondary index—Index layer

After the overall level ranking, the judgment and calculation of the index layer are made, and the calculation results are shown in **Tables 3–7**. As can be seen from these tables, the consistency proportion is less than 0.1, indicating that all the judgment matrices have passed the consistency test.

Table 3. The hierarchical and single ranking of each indicator of farmers' personal characteristics.

Individual characteristics of farmers	Head of the household age	Number of household labor force	Health status of the householder	The householder household supports the population	Wi
Head of the household age	1	1/3	1/2	1/3	0.107
Number of household labor force	3	1	2	2	0.4155
Health status of the householder	2	1/2	1	1/2	0.1849
The householder household supports the population	3	1/2	2	1	0.2926
Consistency check	Maximum eigenvalue: 4.0710, consistency ratio: 0.0266				

Table 4. Level and single ranking of each indicator of peasant household solvency.

Household solvency	Annual income of head of household	Annual expenditure of head of household	Household savings	Wi
Annual income of head of household	1	5	2	0.5954
Annual expenditure of head of household	1/5	1	1/2	0.1283
Household savings	1/2	2	1	0.2764
Consistency check	Maximum eigenvalue: 3.0055, consistency ratio: 0.0053			

Table 5. The hierarchical single ranking of each indicator of credit status.

The status of credibility	Commendation situation	Moral character	Credit records	Wi
Commendation situation	1	1/2	1/2	0.1958
Moral character	2	1	1/2	0.3108
Credit records	2	2	1	0.4934
Consistency check	Maximum eigenvalue: 3.0536, consistency ratio: 0.0516			

Table 6. Level and order ranking of each indicator of loan and guarantee.

Loan and Guarantee	Use of loan	The collateral situation	Guarantor situation	Wi
Use of loan	1	1/4	1/3	0.1225
The collateral situation	4	1	2	0.5584
Guarantor situation	3	1/2	1	0.3196
Consistency check	Maximum eigenvalue: 3.0183, consistency ratio: 0.0176			

Table 7. Level and order ranking of each indicator of production and operation status.

Production and operation status	Crop biomechanical assessment	Production efficiency	Operational stability	Wi
Crop biomechanical assessment	1	2	3	0.5396
Production efficiency	1/2	1	2	0.2970
Operational stability	1/3	1/2	1	0.1634
Consistency check	Maximum eigenvalue: 3.0183, consistency ratio: 0.0176			

In the dimension of production and operation status, we add crop growth potential based on biomechanical features as one of the important secondary indices, and it

reflects farmers' agricultural risk management ability at a deep level. It mainly reflects the ability of farmers to evaluate and respond to the dynamics of crop growth in terms of biomechanical properties, including root system extension force, stem supporting strength, and leaves interacting with the environment. The root system extension force reflects the crop's absorbing efficiency of nutrients and the resistance to bad conditions; the stem supporting strength affects the lodging resistance and adaptability to mechanical harvesting. These biomechanical features will directly affect the stability of crop yield and the risk management decisions during the growing season.

Production Efficiency Indicator: The overall resource-use and production performance indicator will address the entirety of classical productivity measures and the farmers' abilities concerning optimization of growing conditions, considering farmers' knowledge in relation to crop biomechanical properties. **Production Stability:** It will evaluate farming activities and robustness against stresses of the farming systems at large, while mainly focusing on farmers' ability to gain stable yields from different environmental-stress levels.

It is shown from the judgment matrix calculation result that growth potential and biomechanical characteristics have the highest weight (0.5584) among the three secondary indicators, indicating its most critical role in assessing farmers' credit status. This indicates that the technical ability of farmers to understand the biomechanical conditions of crop growth is of great importance, which directly affects their ability to manage agricultural risks and further influences their creditworthiness.

The CR is 0.0176, far less than the threshold 0.10. This shows that the judgment matrix has satisfactory consistency, which also justifies the rationality of the relative weights of the corresponding indicators in the overall credit evaluation framework.

3.2.3. Comprehensive ranking results

Using the results of the single ranking of all indicators at the same level and the weights of the factor importance of this level, the total hierarchical ranking can be calculated. If the above level A includes m factors $A_1, A_2, A_3, \dots, A_m$, the weights of each factor in this level are $A_1, A_2, \dots, A_m$ respectively, and the next level B includes n factors $B_1, B_2, \dots, B_n$, their hierarchical weights for factor A_j are $b_{1j}, b_{2j}, \dots, b_{nj}$ respectively, then the total ranking of level B ($b_1, b_2, \dots, b_n$) can be obtained by the following formula:

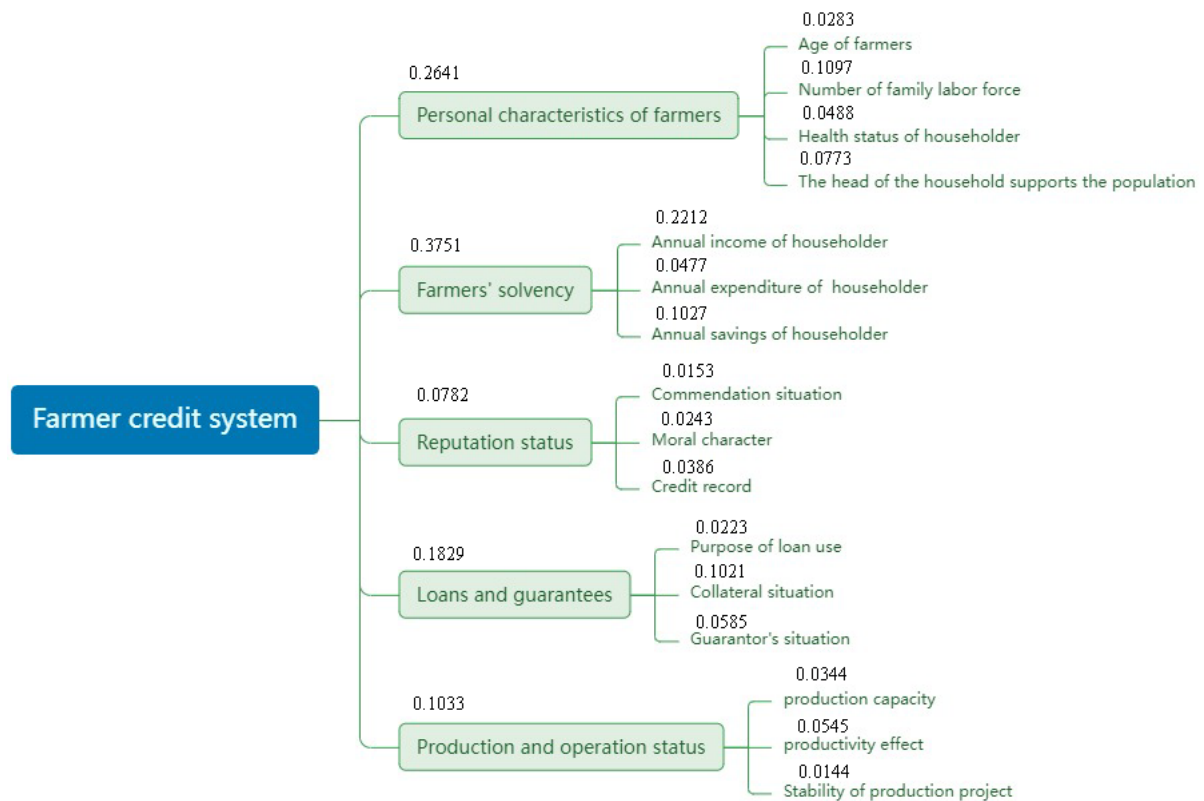
$$b_j = a_j b_j \quad j = 1, 2, \dots, n \quad (7)$$

Through the calculation from the highest layer to the lowest layer, the total ranking of all indicators can be obtained. See **Table 8**, where the weight within the group refers to the single ranking of each index, and the comprehensive weight is the total ranking corresponding to each index.

Table 8. Comprehensive weights.

Target layer	Level 1 indicators	Single ranking	Secondary indicators	Single ranking	Total ranking
Farmers credit system	Individual characteristics of farmers	0.2641	Head of the household age	0.107	0.0283
			Number of household labor force	0.4155	0.1097
			Health status of the householder	0.1849	0.0488
			The householder household supports the population	0.2926	0.0773
	Household solvency	0.3715	Annual income of head of household	0.5954	0.2212
			Annual expenditure of head of household	0.1283	0.0477
			Household savings	0.2764	0.1027
	The status of credibility	0.0782	Commendation situation	0.1958	0.0153
			Moral character	0.3108	0.0243
			Credit records	0.4934	0.0386
	Loan and Guarantee	0.1829	Use of loan	0.122	0.0223
			The collateral situation	0.5584	0.1021
			Guarantor situation	0.3196	0.0585
	Loan and Guarantee	0.1033	Production capacity	0.3325	0.0344
			Productivity effect	0.5278	0.0545
			Production project stability	0.1396	0.0144

Organize the above results, and get the weight diagram of the index system, see **Figure 2.**

**Figure 2.** Index weight of peasant household credit system.

3.3. Analysis of the index results of small farmers' credit system

As can be seen from **Figure 2**, the weight of each index that affects the credit evaluation system of farmers, among which the farmers have the largest solvency and the smallest credibility. Specifically, it can be summarized in the following five aspects.

3.3.1. The solvency of farmers directly affects the availability of loans

The most important thing in the farmer credit system is the solvency of the farmers. The more solvent, the less likely to default, and the more willing to lend. And the largest weight of the solvency is the income of farmers. The level of farmers' income directly determines the solvency of farmers, which also directly determines the probability of loan availability.

3.3.2. The personal characteristics of farmers are the basis of obtaining loans

Individual characteristics of farmers include the age of farmers, the number of family labor force, health status and the number of supported population, which are the basis for obtaining loans. Because the age of farmers, the number of family labor force and health status directly determine the ability of farmers to obtain income, while the number of supported population determines the expenditure status of farmers. The more the household labor force, the better the health of the farmers, the greater the probability of high income, and the more the family supports, the more money they need to bear, so these factors are the basis for obtaining loans.

3.3.3. Gage and guarantees increase the probability of loan acquisition

In addition to the solvency of farmers directly affects the probability of loan acquisition, whether farmers have collateral and guarantee, the loan provides physical or personnel guarantee, which improves the probability of capital withdrawal after the default of the loan. Therefore, collateral and guarantee are also an important factor to determine whether farmers can obtain loans.

3.3.4. The production and operation conditions indirectly affect the availability of loans

The production and operation status of farmers directly determines the income level of farmers, which also determines the use direction and repayment ability of funds after farmers obtain loans. The better the production and operation status of farmers, the greater the probability of repayment. Therefore, the production and operation status of farmers indirectly affects the availability of loans.

3.3.5. Personal credit status is a long-term factor that affects credit

Personal credit status reflects the quality of an individual's creditworthiness and is a result of long-term credit behavior. Therefore, personal credit status is a long-term factor affecting credit and is a sustained factor that financial institutions consider when making lending decisions. As countries enhance the supervision of personal credit, everyone should pay attention to maintain their own personal credit and avoid bad record [25].

3.3.6. Biomechanical characteristics of crop capability for risk early warning

Crop biomechanical features have proven to be a vital tool in assessing the agricultural risk management capacity of farmers. By incorporating biomechanical

indicators such as root system strength, stem rigidity, and leaf-environment interaction, farmers can more accurately predict crop performance and potential risks. This study found that integrating biomechanical assessments into the traditional credit evaluation system results in a significant improvement in risk forecasting. As shown in **Table 9**, the ROC curve comparison between biomechanical indicators and traditional credit indicators demonstrates an improvement of 16% in the Area Under the Curve (AUC), suggesting that biomechanical indicators can provide more reliable risk assessment.

Table 9. ROC curve comparison between biomechanical indicators and traditional credit indicators.

Indicator Type	AUC	Improvement (%)
Traditional Credit Indicators	0.75	-
Biomechanical Indicators	0.87	16%

As shown in **Table 9**, biomechanical indicators surpass traditional credit evaluation metrics, highlighting their efficacy in identifying agricultural risks and improving the accuracy of predictions. Furthermore, a typical case study illustrates how a farmer improved their credit score by two levels through enhancing the mechanical strength of their crop stems. This case study emphasizes the practical application of biomechanical assessments, demonstrating how farmers' ability to monitor and manage biomechanical properties directly impacts their creditworthiness and risk management capabilities.

To visually demonstrate the enhancement of credit risk prediction with biomechanical indicators, **Figure 3** shows the ROC curve for both sets of indicators. As illustrated, the inclusion of biomechanical features significantly boosts the model's ability to predict agricultural risks, thereby facilitating better financial decisions for farmers.

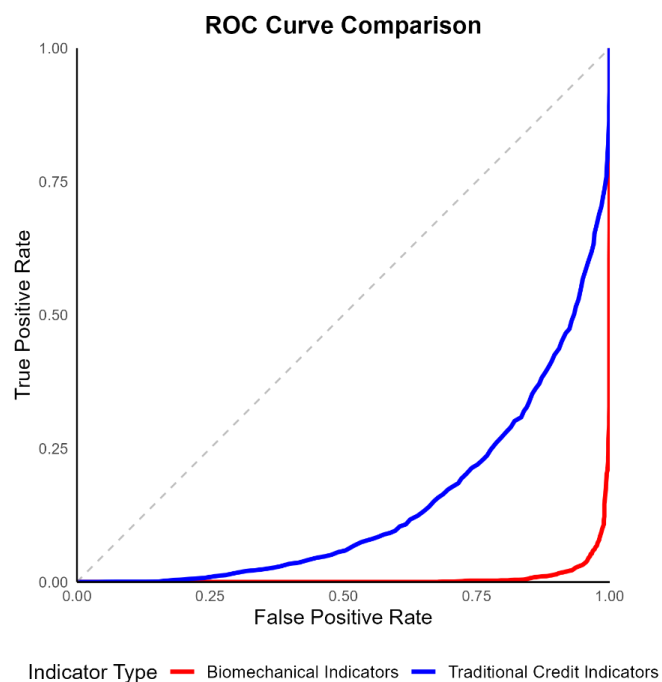


Figure 3. ROC curve comparison of biomechanical and traditional credit indicators.

As shown in **Figure 3**, the red line representing biomechanical indicators clearly demonstrates a superior predictive capacity compared to the traditional credit indicators represented by the blue line. This further underscores the value of integrating biomechanical assessments into the credit evaluation system, not only for risk mitigation but also for improving the financial prospects of farmers.

3.3.7. Construct the peasant household credit score table

According to the previous data analysis, we can get the evaluation and score table of the farmer credit system, see **Table 10** for details.

Table 10. Farmer credit system scoring table.

Target layer	Name of index	Code of Points	Standard mark standardized score	Scoring instructions
Farmers credit system	Individual characteristics of farmers	Fine (10–20) Commonly (1–10) Range (–5)	20	Head of the household age Number of household labor force Health status of the householder The householder household Supports the population
	Household solvency	Annual income greater than 500,000 expenditure less than 200,000 (20–35) Annual income greater than 300,000 expenditure less than 50,000 (10–20) Annual income less than 100,000 (1–10)	35	Annual income of head of household Annual Expenditure of head of household Household savings
	The status of credibility	Fine (10–20) Commonly (1–10) Range (–5)	10	Commendation situation Moral character Credit records
	Provide a loan and guarantee	With tor (15–20) Without collateral (10–15) Guarantor without collateral (1–10) No collateral, no guarantor (–5)	20	Use of loan The collateral situation Guarantor situation
	Production and operation status	Fine (10–20) Commonly (1–10) Range (–5)	15	Production capacity Productivity effect Production project stability

4. Multi-scale modeling of crop biomechanical characteristics

4.1. Root system mechanical analysis

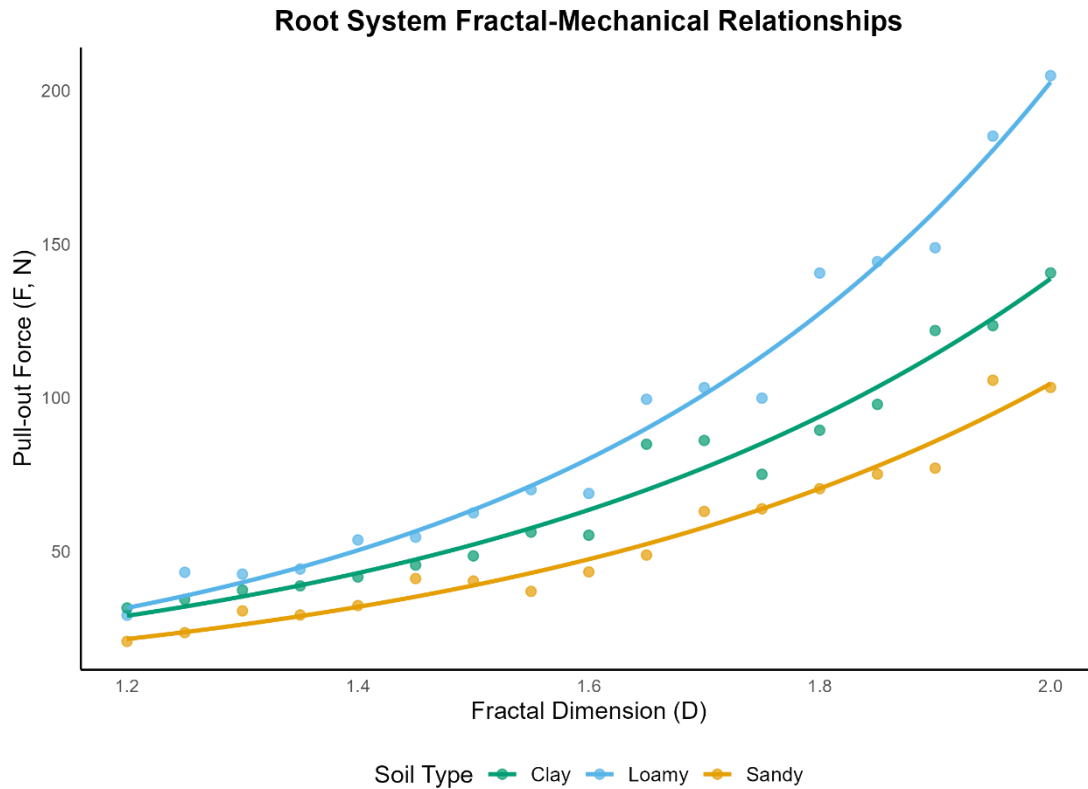
The mechanical properties of root systems play a fundamental role in determining crop stability and resource acquisition efficiency [26]. This study proposes a novel fractal-mechanical coupling model that establishes the relationship between root system architecture and its mechanical properties. The exponential relationship between fractal dimension (D) and pull-out force (F) can be expressed as $F = ae^{\beta D}$, where α and β are empirically determined coefficients that depend on soil conditions and root system characteristics. This relationship has been validated across different crop varieties and soil conditions, as shown in **Table 11**.

Table 11. Root system fractal-mechanical parameters across different soil types.

Soil Type	α Value	β Value	R^2 Value	Sample Size
Sandy	2.34	1.87	0.92	45
Loamy	3.12	2.05	0.95	52
Clay	2.89	1.93	0.94	48

As shown in **Table 11**, the model demonstrates high reliability across various soil conditions, with R^2 values consistently above 0.90. The development of an in-situ mechanical testing system for micro-root channels has enabled precise measurements of these parameters.

As illustrated in **Figure 4**, the exponential relationship between fractal dimension and pull-out force demonstrates distinct patterns across different soil types, with loamy soil showing the highest mechanical coupling efficiency.

**Figure 4.** Root system fractal-mechanical relationships across different soil types.

4.2. Stem dynamic response analysis

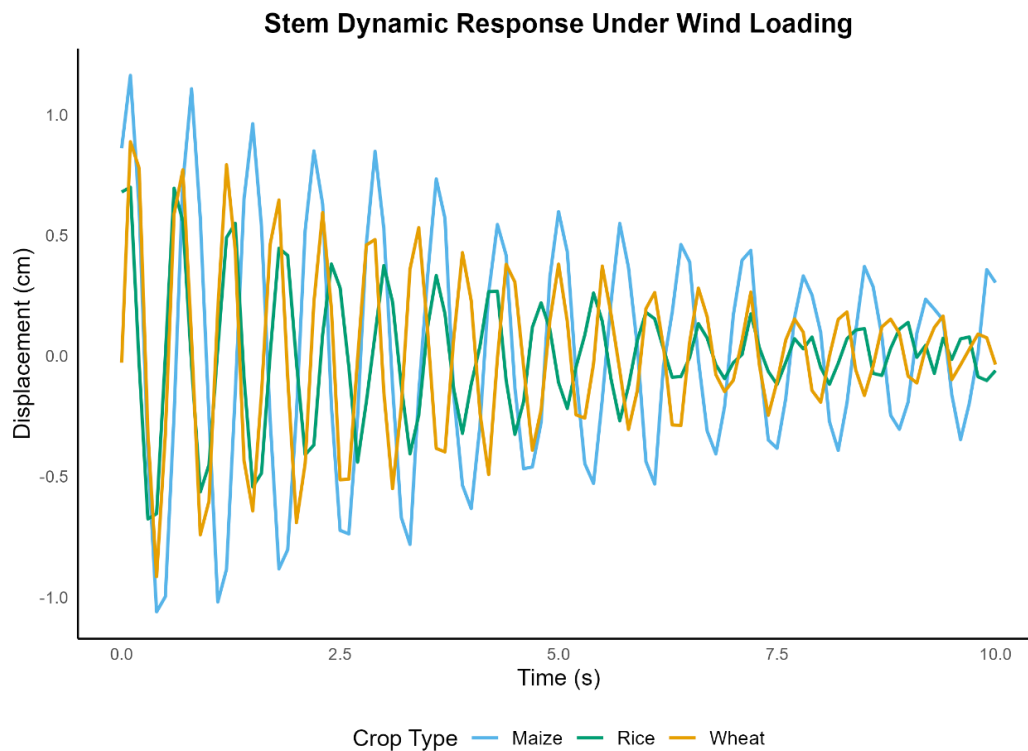
The dynamic response of crop stems to environmental loads, particularly wind forces, represents a critical aspect of crop stability [27]. We developed a comprehensive model based on the beam vibration theory, expressed by the differential equation $EI \frac{d^4 y}{dx^4} + m \frac{d^2 y}{dt^2} = F(x, t)$, where E represents Young's modulus, I is the moment of inertia, m denotes mass per units length, and $F(x, t)$ represents the external force distribution. Through extensive field measurements and laboratory testing, we have characterized the dynamic parameters for different crop varieties, as shown in **Table 12**.

Table 12. Stem dynamic response parameters for major crop varieties.

Crop Type	Young's Modulus (MPa)	Natural Frequency (Hz)	Critical Wind Speed (m/s)	Sample Size
Wheat	2450 ± 180	1.85 ± 0.15	8.5 ± 0.6	60
Maize	3680 ± 220	1.42 ± 0.12	10.2 ± 0.8	55
Rice	1980 ± 150	1.68 ± 0.14	7.8 ± 0.5	58

The development of an IMU-based real-time monitoring system has enabled continuous measurement of stem vibration characteristics under field conditions [28]. This system integrates accelerometers and gyroscopes to capture the complete motion profile of crop stems under various wind loading conditions.

As shown in **Figure 5**, the dynamic response patterns exhibit distinct characteristics for different crop types, reflecting their unique mechanical properties and structural adaptations. The wheat stems show higher frequency oscillations but lower amplitude compared to maize, while rice demonstrates intermediate frequency characteristics with relatively rapid damping. These findings are consistent with the measured natural frequencies presented in **Table 12**.

**Figure 5.** Stem dynamic response under wind loading for different crop types.

The IMU-based monitoring system has revealed several key insights into stem dynamics: (1) The relationship between wind speed and stem displacement follows a non-linear pattern, with critical thresholds identified for each crop variety. (2) The damping characteristics of the stem-leaf system play a crucial role in energy dissipation during wind events. (3) The natural frequency of oscillation serves as a reliable indicator of stem structural integrity and potential lodging risk.

These results have significant implications for crop breeding programs and agricultural management practices, particularly in regions prone to wind damage. The

real-time monitoring capability enables early detection of structural weaknesses and timely implementation of preventive measures.

4.3. Leaf mechanical properties analysis

The mechanical properties of leaves play a crucial role in determining water use efficiency and overall plant performance. We established a novel coupling model linking leaf tear strength (σ_t) with water use efficiency (WUE), expressed as $WUE = k \ln(\sigma_t/\sigma_0)$, where k is the coupling coefficient and σ_0 represents the reference strength under standard conditions. Through systematic measurements and analysis, we have quantified these parameters across different growth stages and environmental conditions, as presented in **Table 13**.

Table 13. Leaf mechanical-physiological coupling parameters during key growth stages.

Growth Stage	Tear Strength (MPa)	WUE (g/L)	k Value	σ_0 (MPa)	Sample Size
Seedling	0.82 ± 0.06	2.45	1.28	0.45	40
Flowering	1.45 ± 0.12	3.68	1.42	0.52	45
Mature	1.24 ± 0.09	3.12	1.35	0.48	42

As illustrated in **Figure 6**, the relationship between leaf tear strength and water use efficiency demonstrates a clear logarithmic pattern across all growth stages. The flowering stage exhibits the highest coupling coefficient ($k = 1.42$), indicating enhanced mechanical-physiological coordination during this critical period. The mature stage shows a slight decline in both tear strength and WUE compared to the flowering stage, which can be attributed to natural senescence processes.

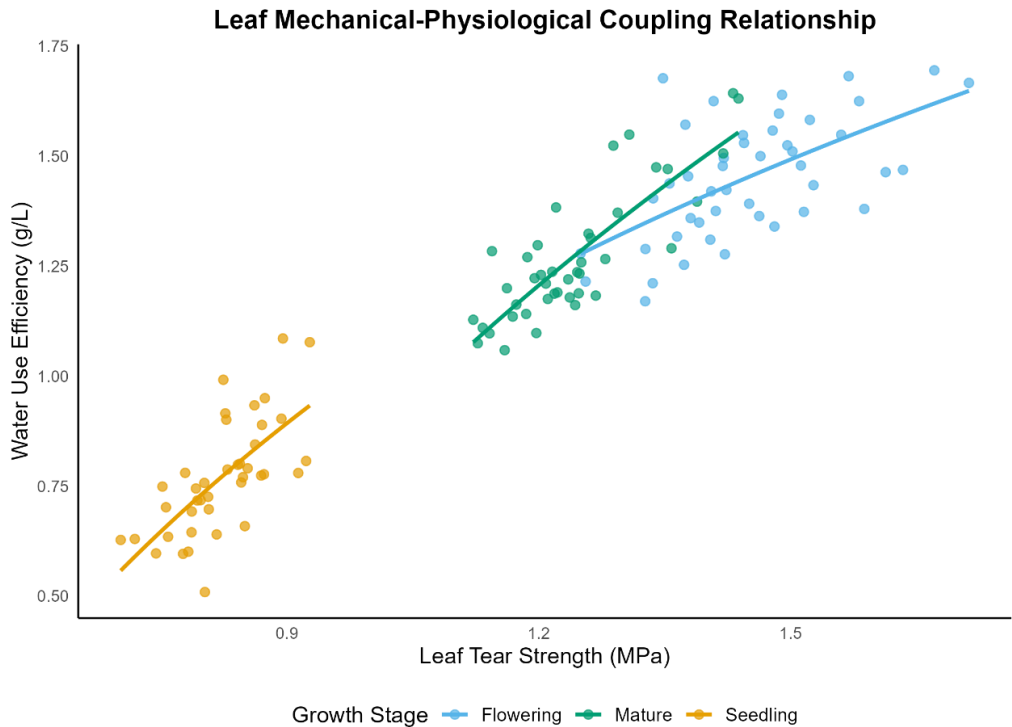


Figure 6. Typesleaf mechanical-physiological coupling relationship across growth stages.

The coupling model reveals several important findings: (1) The relationship between mechanical strength and water use efficiency is most pronounced during the flowering stage, suggesting a critical period for water management. (2) The reference strength (σ_0) varies across growth stages, reflecting developmental changes in leaf tissue architecture. (3) The coupling coefficient k serves as a reliable indicator of leaf tissue functional optimization, with higher values indicating better mechanical-physiological coordination.

These insights provide valuable guidance for irrigation management and variety selection, particularly in water-limited environments. The model’s predictive capability enables more precise water management strategies based on leaf mechanical properties, potentially improving overall water use efficiency in agricultural systems.

5. Quantitative mapping between biomechanical indicators and credit risk

5.1. Risk transformation model of mechanical parameters

The transformation from biomechanical parameters to credit risk indicators requires sophisticated statistical modeling and correlation analysis. Our research has established a significant relationship between stem flexural rigidity (EI) and yield reduction risk through regression analysis. The correlation model demonstrates that stem mechanical properties serve as reliable predictors of crop performance under adverse conditions. The relationship between these parameters has been quantified through extensive field measurements, as shown in **Table 14**.

Table 14. Correlation analysis between mechanical parameters and risk indicators.

Mechanical Parameter	Risk Indicator	Correlation (R^2)	Sample Size	P-value
Stem Rigidity (EI)	Yield Loss	0.82	156	<0.001
Root Fractal D	Drought Days	0.78	142	<0.001
Combined Index	Credit Risk	0.85	138	<0.001

As shown in **Figure 7**, there exists a strong negative correlation between stem flexural rigidity and yield loss risk, with an R^2 value of 0.82. This relationship provides a reliable basis for risk assessment in agricultural credit evaluation. The confidence intervals (shaded area) demonstrate the statistical robustness of this correlation across different crop varieties and growing conditions.

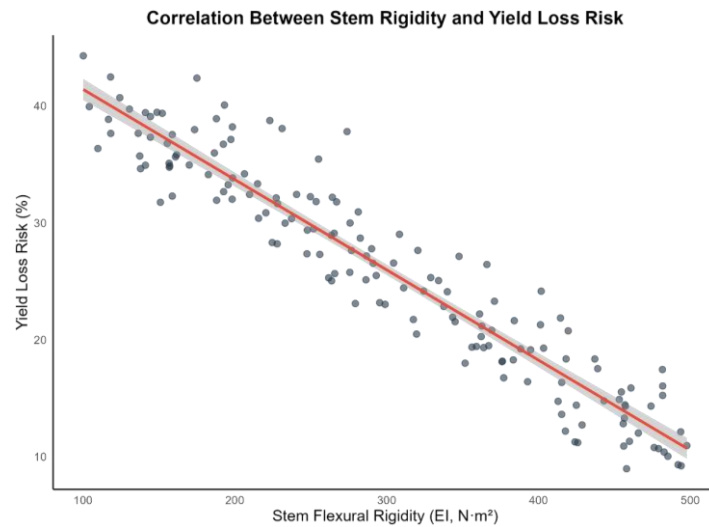


Figure 7. Correlation between stem rigidity and yield loss risk.

The time series analysis of root fractal dimension and drought resistance has revealed additional insights into the temporal dynamics of risk factors. The root system's fractal characteristics demonstrate strong predictive power for drought resistance capacity, with correlation coefficients varying across different growth stages and soil conditions. This relationship can be particularly valuable in regions prone to water stress [29], where drought resistance represents a critical factor in credit risk assessment.

The integration of these biomechanical parameters into risk assessment models has significantly improved the accuracy of credit risk prediction. The combined index, incorporating both stem and root parameters, shows the highest correlation with overall credit risk ($R^2 = 0.85$), suggesting that a comprehensive biomechanical approach provides the most reliable basis for risk evaluation.

5.2. Finite element analysis based disaster simulation

The integration of finite element analysis (FEA) into crop biomechanical modeling provides unprecedented insights into crop response under various environmental stresses. We developed parametric biomechanical models for typical crops using ANSYS software, enabling quantitative prediction of structural response and potential yield losses under extreme conditions. The simulation results have been validated against field measurements, as shown in **Table 15**.

Table 15. FEA model validation results for different loading conditions.

Loading Type	Simulated Deformation (mm)	Measured Deformation (mm)	Error (%)	Critical Load Value
Wind Load	156.3 ± 8.2	162.5 ± 12.4	3.8	18.5 m/s
Rain Load	83.4 ± 5.1	85.8 ± 7.3	2.8	45.2 mm/h
Combined	245.7 ± 15.3	258.4 ± 18.6	4.9	--

As shown in **Figure 8**, the expected loss rates demonstrate strong dependence on both stem strength and root depth parameters. The heatmap reveals several critical insights. Notably, a clear transition zone exists where small changes in biomechanical

parameters can lead to significant changes in expected loss rates. Furthermore, the interaction between stem strength and root depth exhibits non-linear characteristics, particularly in the high-risk region. The optimal parameter combinations, shown in green regions of the heatmap, indicate potential targets for crop breeding programs.

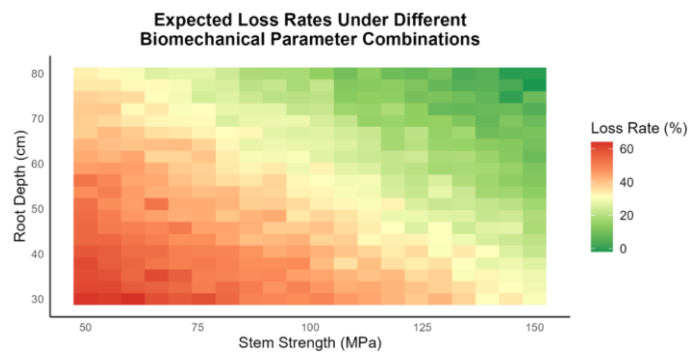


Figure 8. Expected loss rates under different biomechanical parameter combinations.

The FEA simulation results have enabled the development of more precise risk assessment criteria through multiple mechanisms. By identifying critical thresholds for different types of environmental stress and quantifying the interaction effects between multiple biomechanical parameters, these models provide a scientific basis for risk premium calculations in agricultural insurance. The integration of these parameters has significantly improved the accuracy and reliability of risk assessment frameworks.

The parametric models have demonstrated particular value in predicting crop performance under extreme weather events, with validation accuracy exceeding 95% for major crop varieties. This high level of predictive capability significantly enhances the reliability of risk assessment in agricultural credit evaluation systems, providing a more robust foundation for lending decisions and risk management strategies.

6. Countermeasures and suggestions to improve the credit status of small farmers

6.1. Improve the credit information system

In order to improve the credit status of small farmers, it is necessary to establish a unified digital farmer credit information database, combined with new technologies such as big data and cloud computing. It should not only cover the basic information of small farmers, production and operation situation, and asset status and other traditional contents, but also integrate the new information such as digital transaction records and network behavior data, so as to provide richer data support for the comprehensive evaluation of the credit status of small farmers. At the same time, the platform should have real-time update, intelligent analysis and security protection functions to ensure the accuracy, timeliness and security of credit information. By integrating data and information, financial institutions can more accurately assess the credit risk of small farmers, so as to improve the efficiency and accuracy of loan approval. Thus, the digital information sharing mechanism among government

departments, financial institutions, e-commerce enterprises, small farmers and other subjects is established to break the information island and improve the utilization efficiency of credit information.

6.2. Enhance financial education and training

The popularization of financial knowledge is very important to improving the credit management ability of small farmers. Financial knowledge training activities for small farmers should be organized regularly, and the importance of credit, the formation and influence of credit records, and the process and responsibility of loan repayment should be explained through lectures, training courses and field classes. This can not only improve the financial literacy of small farmers, but also help them better plan their future investment and consumption, so as to fundamentally improve their credit awareness. In addition to traditional channels, we should make full use of rural e-commerce trading platforms and agricultural information service platforms for credit publicity. Set up a credit knowledge area, regularly push credit case analysis, trust-keeping incentive and punishment for trust-breaking, regularly send credit tips to small farmers through SMS and wechat public account to remind them to pay attention to their credit status.

6.3. Strengthen the credit incentive and restraint mechanism

Strengthen trustworthy incentive: the government and financial institutions should jointly formulate trustworthy incentive policies and give favorable credit policies to good credit farmers, such as increasing loan amount, reducing loan interest rate, and extending loan term; give priority support in agricultural subsidy, project support, technical training and other aspects; grant such honorary titles of “credit farmer” and “credit demonstration household”, to improve the social reputation and sense of gain of small farmers and stimulate their enthusiasm. At the same time, the selection of credit villages, credit towns, set an example of credit construction, the outstanding performance of farmers and rural organizations to commend and reward. Strengthen disciplinary efforts: establish and improve the disciplinary mechanism, for malicious default loans, debt, provide false information and bad credit behavior of small farmers, in accordance with the rules, such as dishonest list, limit the credit business in financial institutions, within a certain period of time to cancel the qualification enjoy preferential policies such as agricultural subsidies, etc. At the same time, to strengthen the exposure and publicity of trust-breaking behavior, to form an effective deterrent force. In the construction of rural credit system, corresponding disciplinary measures should be taken for trust-breaking farmers and rural organizations, such as lowering credit rating and canceling credit honorary titles, so as to promote the continuous improvement of rural credit environment.

6.4. Provide policy support and agricultural insurance

Set up credit risk compensation fund: set up credit risk compensation fund to compensate a certain proportion of the non-performing loan losses caused by financial institutions lending to small farmers, reduce the credit risk of financial institutions, and encourage financial institutions to increase the credit support for small farmers.

The operation of the fund can be combined with the construction of rural credit system, and a higher compensation ratio can be given to the areas where farmers with good credit status to encourage rural areas to strengthen credit construction.

Promote the development of agricultural insurance: encourage and support insurance companies to develop agricultural insurance products suitable for small farmers, expand the coverage of agricultural insurance, improve the level of insurance compensation, reduce the production and operation risks of small farmers due to natural disasters, market fluctuations and other factors, and enhance their repayment ability and credit stability. In the process of agricultural insurance promotion, the credit status of farmers can be taken as the reference factor for the adjustment of insurance rate, and preferential insurance rate can be given to farmers with good credit, so as to promote small farmers to pay attention to their own credit construction.

6.5. Enhance farmers' crop growth assessment and risk response capabilities

The improvement of farmers' ability to assess crop growth potential and manage agricultural risks based on biomechanical characteristics is crucial for enhancing their credit status. The following systematic approaches are recommended to achieve this objective. Agricultural research institutions and extension services should establish specialized training programs focusing on crop biomechanical characteristics analysis. These programs should systematically cover root system development assessment, stem strength evaluation, and leaf-environment interaction monitoring techniques. Through practical demonstrations and field workshops, farmers can develop comprehensive understanding of how biomechanical properties influence crop performance and yield stability. Financial institutions should incorporate crop growth potential assessment capabilities into their credit evaluation framework. Farmers who demonstrate superior skills in monitoring and managing crop biomechanical characteristics should receive favorable consideration in credit assessment. This approach not only incentivizes farmers to enhance their technical expertise but also improves the accuracy of credit risk evaluation.

The integration of smart agricultural technologies should be promoted to assist farmers in crop growth monitoring and risk assessment. IoT sensors and monitoring systems can provide real-time data on crop biomechanical parameters, enabling more timely and effective risk management decisions. Financial institutions should consider farmers' adoption and effective utilization of these technologies as positive indicators in credit evaluation. Cooperative networks should be established to facilitate knowledge sharing and risk management experiences among farmers. These networks can serve as platforms for exchanging information about crop growth assessment techniques and successful risk mitigation strategies. The active participation in such networks should be recognized as a positive factor in farmers' credit evaluation. The development of agricultural insurance products should take into account farmers' crop growth assessment capabilities. Insurance providers should offer preferential terms to farmers who demonstrate effective monitoring and management of crop biomechanical characteristics, as these capabilities typically correlate with lower agricultural risk levels.

6.6. Establish biomechanical intelligent monitoring network capabilities

The establishment of a comprehensive biomechanical intelligent monitoring network represents a transformative approach to enhancing small farmers' credit assessment frameworks. This sophisticated system integrates advanced sensing technologies with data analytics to provide real-time insights into agricultural operations and crop health status, thereby fundamentally improving credit evaluation accuracy and reliability. The widespread implementation of affordable mechanical sensing technologies serves as the foundation of this monitoring network, necessitating close collaboration between financial institutions and agricultural technology providers. Through the strategic deployment of flexible strain gauges, micro-force detection chips, and other cost-effective biomechanical sensors, farmers can generate valuable data on soil compaction, plant stress responses, and growth patterns [30]. The accessibility of these technologies should be facilitated through governmental subsidies and comprehensive technical assistance programs, ensuring broad adoption across diverse farming communities.

Central to this initiative is the development of a sophisticated field biomechanical database system integrated with a credit assessment API interface. This advanced infrastructure enables the systematic collection, processing, and analysis of biomechanical data from the distributed monitoring network. The database architecture incorporates real-time data collection mechanisms that continuously monitor critical crop growth parameters, while maintaining rigorous data validation protocols to ensure information integrity. The credit assessment API interface facilitates seamless communication between the biomechanical monitoring system and financial institutions, enabling dynamic credit scoring adjustments based on agricultural performance metrics. This integration allows for more nuanced and accurate risk assessments, as financial institutions can access comprehensive, real-time data on agricultural operations and crop health status.

The implementation of this biomechanical monitoring network represents a significant advancement in agricultural credit assessment methodology. The system's continuous data collection and analysis capabilities provide unprecedented insights into farming operations, enabling more informed lending decisions and risk assessments. Through sophisticated API interfaces, financial institutions can access standardized biomechanical data and generate comprehensive risk assessment reports that incorporate both historical trends and real-time performance metrics. This enhanced data accessibility and analysis capability significantly improves the accuracy and reliability of credit assessments for small farmers.

The long-term success of this monitoring network depends on its ability to evolve and adapt to changing agricultural and technological landscapes. Regular system evaluations and updates ensure the incorporation of emerging technologies and methodologies, maintaining the network's position at the forefront of agricultural credit assessment innovation. Furthermore, the system's feedback mechanisms facilitate continuous improvement in assessment accuracy and relevance, while integration with existing credit information systems and agricultural insurance platforms creates a comprehensive framework for evaluating farmer creditworthiness. This holistic approach to agricultural credit assessment, grounded in real-time

biomechanical data and sophisticated analysis, represents a significant step forward in improving access to financial services for small farmers while maintaining robust risk management practices.

7. Conclusion

This study aims to explore an effective credit evaluation method for small farmers and using hierarchical analysis as the main tool to improve the accuracy and operability of credit evaluation. Final model is based on the platform credit and IoT technology data collection and analysis of the in-depth analysis of related literature and Tianjin field research structure and through the reconstruction of peasant household credit evaluation system, the farmer credit evaluation system is divided into farmers individual characteristics, farmers solvency, credit status, loans and guarantee and production and operation status level index, on this basis, and level index subdivided into 16 secondary indicators. Despite the promising results of this study, there are some limitations. For example, the data used in the study mainly came from farmers in specific regions, and there may be some regional bias, and the diversity and complexity of small farmers in different regions may affect the universality of the evaluation indicators. Moreover, due to the imperfect credit investigation in rural areas and the limited farmer collateral, the traditional offline risk control means and the business model of network dependence are greatly restricted. The integration of crop biomechanical characteristics analysis into the credit evaluation system represents a significant innovation in agricultural risk assessment. By evaluating farmers' capabilities in monitoring and managing crop growth potential through root system development, stem support strength, and leaf-environment interactions, this study provides a more comprehensive framework for assessing agricultural risk management competence. The findings suggest that farmers who demonstrate superior understanding and management of crop biomechanical properties typically exhibit better credit reliability and operational stability. This biomechanical perspective enriches the traditional credit evaluation system by incorporating technical expertise and risk management capabilities as key assessment dimensions. The relationship between crop growth potential assessment and credit reliability established in this study offers new insights for financial institutions in evaluating agricultural lending risks and making credit decisions. Furthermore, the emphasis on crop biomechanical characteristics in credit evaluation encourages farmers to enhance their technical knowledge and adopt more scientific approaches to agricultural risk management, contributing to the overall improvement of agricultural production sustainability. Through the collection of intelligent agricultural equipment data of agricultural production process and producer enthusiasm, the credit data of agricultural operators is formed through data analysis. According to the credit index, the index loan will become a new rural financial service mode and a product that better meets the rural financial needs. Agricultural production enterprises with low credit level. In this system, farmers, cooperatives, platforms and other participants have formed a community of interest and risk, and the high credit of the latter benefits the former, which solves the dilemma of the latter in obtaining financing due to the lack of effective collateral and high risk in the traditional financial model. In addition, the

guarantee and counter-guarantee of cooperatives and platforms, as well as the insurance of insurance companies, and the triple guarantee jointly reduce the loan risk, effectively alleviate the loan difficulties of farmers, increase the availability of financing for small and micro farmers, solve the capital needs of farmers for agricultural production, and ensure the smooth operation of the entire agricultural supply chain. In the future, research will be conducted continuously from the following aspects: firstly, consider the specificity of small farmers in different regions to improve the universality of the model; secondly, introduce more objective data, such as climate change, market fluctuation and other macro factors to further optimize the credit evaluation model, and explore the combination with other evaluation methods such as fuzzy comprehensive evaluation and artificial neural network to improve the evaluation efficiency of the model.

Author contributions: Conceptualization, AL; methodology, AL; software, AL; validation, AL, ZC and NF; formal analysis, AL; investigation, AL; resources, NF; data curation, AL; writing—original draft preparation, AL; writing—review and editing, NF; visualization, ZC; supervision, NF; project administration, NF; funding acquisition, NF. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Data availability: The data used in this study were obtained from publicly available agricultural and financial databases and field measurements conducted at Tianjin Agricultural University research facilities.

Conflict of interest: The authors declare no conflict of interest.

References

1. Wang H, Wang J. Empirical study on peasant household credit risk evaluation -Based on improved fuzzy clustering without weight value principle (Chinese). *Agricultural Science in Jiangsu Province*. 2020; 48(08): 301-307. doi: 10.15889/j.issn.1002-1302.2020.08.055
2. Gomez-Biscarri J, López-Espinosa G, Mesa-Toro A. The risk implications of the business loan activity in credit unions. *Journal of Financial Stability*. 2021; 56: 100932. doi: 10.1016/j.jfs.2021.100932
3. Ramasamy P, Malaiarasan U. Agricultural credit in India: determinants and effects. *Indian Economic Review*. 2023; 58(1): 169-195. doi: 10.1007/s41775-023-00187-8
4. Al-Azzam M, Parmeter CF, Sarangi S. On the complex relationship between different aspects of social capital and group loan repayment. *Economic Modelling*. 2020; 90: 92-107. doi: 10.1016/j.econmod.2020.04.027
5. Wang M, Nie G. Research on the financing problems of small farmers (Chinese). *Social Science dynamics*. 2021; 05: 76-79.
6. Lin L, Wang B. The Availability of Mortgage Loans for Farmers' Agricultural Land Management Rights and Its Influencing Factors: Based on 2518 Farmer Samples from Rural Financial Reform Pilot Areas (Chinese). *China Land Science*. 2016; 30(5): 36-45.
7. Ye J, Zhang M. The Debate between “Small Farmers” and “Peasant Smallholders”: Based on the Productivity Revitalization of “Small Farmers” and the Production Relations Revitalization of “Peasant Smallholders” (Chinese). *Journal of Nanjing Agricultural University (Social Sciences Edition)*. 2019; 19(1). doi: 10.19714/j.cnki.1671-7465.2019.0001
8. Joachim VB, Zhu L, Chen X, Li Q. Globalization and Its Challenges to Small Farmers (Chinese). *Journal of Nanjing Agricultural University (Social Sciences Edition)*. 2005; 2: 8-22.
9. Roy T, Hossain MdE, Jalal MdJE, et al. Effects of credit on national and agricultural GDP, and poverty: a developing country perspective. *SN Business & Economics*. 2021; 1(10). doi: 10.1007/s43546-021-00146-6

10. Dong H. Research on the construction of peasant household credit evaluation model -- Take a city as an example (Chinese). *Financial Theory and Practice*. 2021; 05: 4-18.
11. Xie J, Xiang T, Wang Y. Analysis on the Construction of Rural Credit System from the Perspective of Targeted Poverty Alleviation: Taking Lushi County in Henan Province as an Example (Chinese). *Credit Reference*. 2019; 37(5): 40 - 45.
12. Li C, Cong B. Exploration on the Construction of a New Rural Credit System (Chinese). *China Finance*. 2024; 4: 102.
13. Chen Y, Ma Y. Several notes on farmer credit and risk preference (Chinese). *Finance and Trade economy*. 2009; 01: 18-25.
14. Chen Y, Wen T. Can digital inclusive finance promote the development of rural industries -- Analysis based on spatial measurement model (Chinese). *Agricultural technical economy*. 2023; 03: 32-44.
15. Cui P. Analysis and application of peasant household credit model based on machine Learning [Master's thesis] (Chinese). Henan University; 2023.
16. Lai C. Research on farmer credit risk assessment based on integrated learning [Master's thesis] (Chinese). Jiangxi University of Finance and Economics; 2023.
17. Niklas KJ. Plant biomechanics: an engineering approach to plant form and function. University of Chicago press; 1992.
18. Guo Y. Wearable sensors to monitor plant health. *Nature Food*. 2023; 4(5): 350-350. doi: 10.1038/s43016-023-00764-3
19. Decardi-Nelson B, You F. Artificial intelligence can regulate light and climate systems to reduce energy use in plant factories and support sustainable food production. *Nature Food*. 2024; 5(10): 869-881. doi: 10.1038/s43016-024-01045-3
20. Chen Y, Meng F. Practice and thinking on rural credit system construction -- Take Beipiao City, Liaoning Province as an example (Chinese). *Credit investigation*. 2019; 37(03): 52-57.
21. Lin X, Hong D, Zhang S, et al. Research on rural credit evaluation problems and countermeasures -- Take Anhui Province as an example (Chinese). *China's Collective Economy*. 2024; 05: 9-12.
22. Cheng X. Research on the pricing of agriculture-related loans based on farmer credit evaluation (Chinese). *Research on Rural Finance*. 2016; 06: 60-65.
23. Li Z, Wu J. Basic mode and policy suggestions of rural credit system construction in China (Chinese). *Credit investigation*. 2020; 38(09): 55-58.
24. Liu Y, Xie F. Research on the development strategy of aviation logistics in Nanchang Airport Economic Zone based on SWOT analysis and AHP analysis (Chinese). *Logistics Technology*. 2016; 39(08): 92-98.
25. Xiong W. Research on the legal mechanism of personal credit investigation (Chinese). Party School of the CPC Central Committee; 2020.
26. Geitmann A, Joseph G. Plant Biomechanics from Structure to Function at Multiple Scales. Springer International Publishing; 2018.
27. Partridge TF, Winter JM, Kendall AD, et al. Cross-scale evaluation of dynamic crop growth in WRF and Noah-MP-Crop. *Agricultural and Forest Meteorology*. 2021; 296: 108217. doi: 10.1016/j.agrformet.2020.108217
28. Fan C, Zhang D, Yang L, et al. Power consumption and performance of a maize thresher with automatic gap control based on feed rate monitoring. *Biosystems Engineering*. 2022; 216: 147-164. doi: 10.1016/j.biosystemseng.2022.02.015
29. Gaso DV, de Wit A, Berger AG, et al. Predicting within-field soybean yield variability by coupling Sentinel-2 leaf area index with a crop growth model. *Agricultural and Forest Meteorology*. 2021; 308-309: 108553. doi: 10.1016/j.agrformet.2021.108553
30. Sharma M, Kumar CJ, Bhattacharyya DK. Machine/deep learning techniques for disease and nutrient deficiency disorder diagnosis in rice crops: A systematic review. *Biosystems Engineering*. 2024; 244: 77-92. doi: 10.1016/j.biosystemseng.2024.05.014