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Research article

The impact of environmental regulations and digital empowerment on agri-food supply chains under stochastic market demand conditions

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Abstract: The green transformation of agri-food supply chains is vital for reducing environmental burdens and ensuring food safety. However, research lacks a comprehensive understanding of how environmental regulations and digital technologies synergistically drive this transformation under market uncertainties and stakeholder behavioral complexities. This research gap limits the development of effective policies and strategies for sustainable agricultural development. To address this gap, we adopted an integrated perspective of environmental regulation and digital empowerment to construct a tripartite evolutionary game model involving farmers, wholesalers, and government. Based on evolutionary game theory and stochastic differential equations, we analyzed how strategies evolve and reach equilibrium under the combined influence of policy interventions, market dynamics, and technological adoption. Through sensitivity analysis of key parameters, the results revealed that green production costs, digital technology costs, market premiums, and regulatory intensity significantly determine the system's evolutionary trajectory. The initial strategy distribution affects convergence speed, while market volatility and bounded rationality may cause fluctuations or destabilization. This research advances theoretical understanding of sustainable transformation mechanisms in agri-food supply chains and provides practical insights for developing resilient green supply systems and targeted agricultural policies.

Keywords: agri-food supply-chain; environmental regulation; digital technology; evolutionary game; sensitivity analysis; numerical simulation
Mathematics Subject Classification: 91A22, 91A80, 65C99, 90B06

1. Introduction

The escalating global environmental crisis, characterized by climate change, resource depletion, and ecological degradation, has emerged as a significant threat to human survival [1,2]. Frequent extreme weather events, land desertification, high carbon emissions, and water scarcity have profoundly impacted global ecosystems, prompting nations to prioritize green development as a core strategy for achieving sustainable development goals [3]. As a cornerstone industry for ensuring food security and supporting the global economy, agriculture faces unprecedented pressure to transition in this context. While modern agriculture has significantly increased food production through technological innovation and large-scale operations, conventional agricultural practices contribute significantly to greenhouse gas emissions through fertilizer application, livestock production, and energy-intensive operations [4]. Moreover, the current agricultural system faces mounting challenges from resource depletion, environmental degradation, and the urgent need for sustainable production methods that can address both food security and climate mitigation goals [5], which are incompatible with the demands of green development.

Environmental changes have particularly far-reaching impacts on agriculture. Shifts in precipitation patterns and the increasing frequency of natural disasters driven by climate warming directly threaten crop growth cycles and yield stability, while resource scarcity escalates production costs, weakening the resilience of agricultural supply chains [6]. As a critical link between production and consumption, the green transformation of agri-food supply chains is pivotal not only for reducing carbon footprints and protecting the environment but also for ensuring food safety, enhancing market competitiveness, and building consumer trust [7–9]. However, traditional supply chains face significant challenges, including information opacity, low management efficiency, and high green production costs, which severely hinder the realization of sustainable development goals [10]. Environmental regulations, as a key governmental tool for promoting green transformation, encourage farmers and enterprises to adopt environmentally friendly practices through stringent emission standards, green subsidies, and tax incentives [10,11], thereby facilitating the transition of supply chains toward green and intelligent systems.

To address these challenges, the rapid development of digital technologies offers new opportunities for the green transformation of agricultural supply chains. Digital empowerment, defined as the strategic application of digital technologies to enhance stakeholders' capabilities, decision-making processes, and operational efficiency within supply chain networks, represents a paradigm shift in agricultural management. In recent years, the widespread adoption of technologies such as blockchain, the Internet of Things (IoT), and big data has significantly transformed the management models and market dynamics of agricultural supply chains [12]. In particular, blockchain technology, with its decentralized, tamper-proof, and highly transparent characteristics, provides robust support for building efficient and trustworthy supply chain systems. By recording data across the process from production to consumption, blockchain ensures the traceability of agri-food quality, reduces information asymmetry, and enhances supply chain coordination efficiency [13,14]. Furthermore, blockchain enables the establishment of credible quality and green certification systems, boosting consumer confidence in green agri-food and significantly increasing their market premiums and demand elasticity [15]. Moreover, IoT enables real-time monitoring of production environments and optimizes resource allocation, while big data analytics facilitates precise matching of supply and demand by analyzing consumer preferences. The integrated application of these technologies amplifies the empowering effects of blockchain, providing a solid foundation for intelligent and precise supply chain management [16].

Despite the synergistic potential of combining environmental regulations with blockchain technology to advance the green agri-food supply chain, its implementation faces complex challenges stemming from market stochastic fluctuations and the irrational behavior of stakeholders.

Agricultural supply chains operate in highly uncertain environments characterized by significant market volatility. Commodity price fluctuations can reach 20–50% annually for major agri-foods, creating substantial planning challenges for supply chain actors [17]. Climate-related disruptions further compound these uncertainties, with extreme weather events affecting agri-foodion across multiple regions and creating ripple effects throughout supply chains [18]. Under such conditions, supply chain stakeholders often exhibit bounded rationality, making decisions based on limited information and cognitive constraints rather than full optimization [19]. Furthermore, opportunistic behavior and information asymmetries between supply chain partners create additional coordination challenges, particularly in the context of implementing new technologies and sustainable practices, thereby complicating strategic choices in green transformation initiatives [20].

Researchers predominantly focus on static analyses, overlooking the profound impacts of market stochastic fluctuations and irrational behavior on the dynamic interactions among stakeholders, as well as the lack of systematic exploration into the synergistic effects of environmental regulations and blockchain technology. To address this, we innovatively incorporate market stochastic fluctuations and irrational behavior, constructing a tripartite evolutionary game model involving farmers, wholesalers, and the government to systematically investigate the dynamic mechanisms, evolutionary paths, and key influencing factors of environmental regulations in driving the digital technology-enabled green agri-food supply chain.

Grounded in the theoretical framework of stochastic evolutionary game theory, we systematically examine how environmental regulations facilitate the empowerment of the green agri-food supply chain through digital technologies, focusing on the dynamic interaction effects between stakeholders' stochastic behavior and market fluctuations in a bounded rationality market. We aim to provide cutting-edge theoretical insights and practical guidance for the green transformation of agriculture. The specific objectives and contributions are as follows: (1) Revealing the Strategy Evolution Law in Bounded Rationality Markets: By constructing a stochastic evolutionary game model involving farmers, wholesalers, and the government, we deeply analyze how market uncertainties interact with stakeholders bounded rational behavior. We characterize the nonlinear evolutionary paths of green production, digital technology adoption, and regulatory strategies, filling the theoretical gap in understanding the interaction mechanisms between stochastic behavior and dynamic uncertainties. (2) Quantifying the Synergistic Effects of Environmental Regulation and Digital Technology: The research elucidates the synergistic mechanisms between environmental regulatory policies and digital technology adoption in bounded rationality markets. We assess their combined impact on the sustainability of green agri-food supply chains, providing a rigorous theoretical basis for policy optimization and technology deployment. (3) Proposing a Dynamic Strategy Framework for Stochastic Environments: Based on stochastic evolutionary game analysis, we extract dynamic optimal strategy combinations for farmers, wholesalers, and the government under conditions of bounded rationality and market fluctuations. Moreover, we provide scientifically feasible guidance for governments to formulate flexible environmental regulation policies and for agricultural stakeholders to implement green transformation, enhancing the resilience and sustainability of the green agri-food supply chain.

Through these research objectives, we not only aim to enrich the theoretical framework at the intersection of green supply chain management and the digital economy but also seek to offer actionable policy recommendations for governments to develop science-based environmental regulations and for agricultural stakeholders to pursue green transformation. Ultimately, it contributes to the sustainable development of the green agri-food supply chain, supporting the realization of agricultural modernization and global green development goals. The research framework of this study is illustrated in Figure 1.

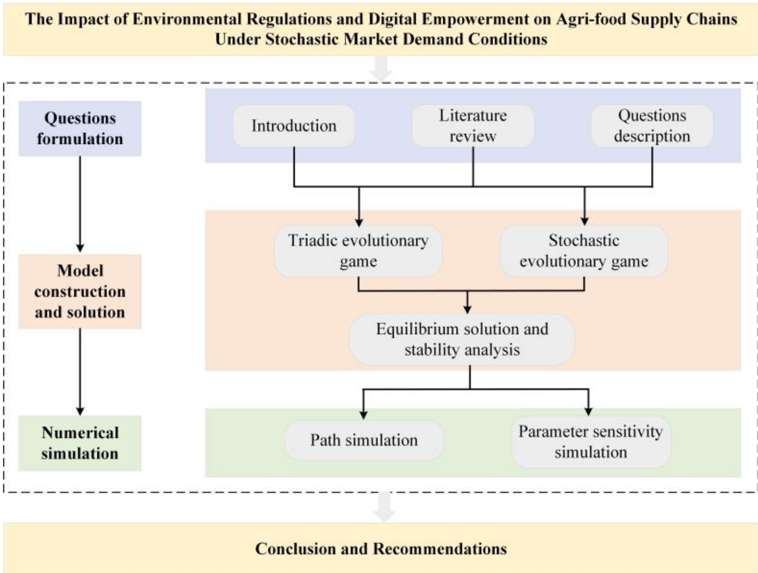

Figure 1. Framework.

2. Literature review

The application of digital technologies in agricultural supply chains encompasses multiple domains, including the Internet of Things (IoT), blockchain, big data analytics, and artificial intelligence (AI). IoT enables real-time monitoring of agri-foodion, transportation, and storage through sensors and smart devices, effectively reducing resource waste and environmental pollution [18]. Blockchain technology ensures transparency and traceability of supply chain data through distributed ledgers, enhancing consumer trust in green agri-food [12]. Big data analytics and AI contribute to reducing the carbon footprint in supply chains by predicting market demand and optimizing logistics routes [21,22]. Collectively, these technologies drive the digital transformation of supply chains, providing a technological foundation for green development. The operational mechanisms of digital technologies in agri-food supply chains have received increasing empirical attention. Research exploring blockchain technology's role in high-value food supply chains reveals that transparency and verifiability of information eliminate opportunistic behavior and increase consumer confidence in food safety and traceability [23]. Studies demonstrate that blockchain integration creates verified information flows, with blockchain-verified provenance enabling producers to charge premium prices for their products, as evidenced by examples where small farms achieved 20% price increases after implementing blockchain traceability [24]. Recent studies have further advanced the understanding of digital technology adoption in agricultural supply chains through game-theoretical approaches. Additionally, research has demonstrated that government support plays a crucial role in facilitating blockchain and IoT adoption in agricultural contexts, where farmers, technology providers, and government agencies engage in strategic interactions to optimize technology deployment and regulatory frameworks [25]. These studies highlight the importance of policy incentives in overcoming initial adoption barriers and achieving network effects in digital agricultural systems.

Environmental regulations, such as carbon taxes and emissions trading schemes, incentivize enterprises to adopt digital technologies to improve resource efficiency and reduce emissions by increasing environmental costs. Studies indicate a positive correlation between the intensity of environmental regulations and corporate investment in digitalization [26]. For instance, government subsidies support enterprises in deploying IoT technologies to achieve precision agriculture and reduce the use of fertilizers and pesticides [27]. In addition, researchers have verified that environmental policy measures have an impact on China's high-carbon emission industries, which may be transmitted to the agricultural products industry through the supply chain. A multi-layer neural network to predict the price trend of European carbon has been tested, showing, that different environmental fluctuations will affect the effectiveness of carbon emission reduction and then spread to carbon prices [28]. Furthermore, the application of blockchain technology under environmental regulations can effectively verify enterprises' compliance with green production standards, lowering regulatory costs [29]. However, research rarely explores how environmental regulations drive the large-scale adoption of digital technologies through tripartite game mechanisms, leaving significant room for further investigation in this area. The integration of carbon footprint considerations into agricultural supply chain management has gained significant attention, with recent game-theoretical models exploring Nash equilibrium solutions for low-carbon implementation strategies [30]. These approaches examine how different stakeholders balance economic objectives with environmental commitments, revealing that cooperative strategies often yield superior environmental outcomes compared to non-cooperative approaches, particularly when supported by appropriate policy mechanisms.

Despite the immense potential of digital technologies in green agri-food supply chains, their application faces multiple challenges. First, the high costs of technology, particularly for small and medium-sized agricultural enterprises, make the initial investment in IoT or blockchain prohibitive [31]. Second, the lack of willingness among upstream and downstream enterprises to share data hinders the synergistic effects of digital technologies [32]. Finally, the low levels of standardization and normalization in digital technology applications lead to inconsistent implementation outcomes [33]. These issues necessitate policy guidance and market mechanisms within the framework of environmental regulations to facilitate resolution.

The green agri-food supply chain emphasizes environmental sustainability across the chain from production to consumption, encompassing green production, green logistics, and green consumption [34]. Its core objective is to achieve a synergy of economic and ecological benefits by optimizing resource allocation and minimizing environmental impact. Studies demonstrate that the implementation of green supply chains significantly enhances the market competitiveness of agri-food while meeting consumer demand for healthy and sustainable products [35]. However, the complexity of green supply chains requires coordinated efforts among multiple stakeholders (producers, logistics providers, retailers, and consumers), with environmental regulations playing a pivotal role in aligning their interests.

Environmental regulations drive the green transformation of agricultural supply chains through command-and-control instruments (e.g., emission standards) and market-based incentives (e.g., green subsidies). Command-and-control regulations compel enterprises to improve production processes to meet environmental standards, thereby fostering green technological innovation [36]. Market-based incentives, such as tax exemptions, encourage enterprises to invest in green logistics and packaging technologies [18]. Moreover, growing consumer environmental awareness amplifies the impact of environmental regulations, prompting enterprises to enhance their brand image through green supply chain management [37]. While existing studies predominantly focus on the impact of environmental regulations on individual enterprises, dynamic analyses of the overall evolutionary path of supply chains, particularly from a tripartite game perspective, remain scarce.

The evolution of green agri-food supply chains is driven by the interplay of technological advancements, market demand, and policy environments. Evolutionary game theory provides an effective framework for analyzing the strategic choices of stakeholders within the supply chain [38]. Studies indicate that the green decision-making of supply chain enterprises is shaped by a combination of cost-benefit considerations, competitive pressures, and policy incentives [39]. Under environmental regulations, supply chains may undergo an evolutionary process from traditional models to partial greening and, ultimately, to full greening [18]. The introduction of digital technologies further accelerates this process; for instance, blockchain enhances supply chain transparency, bolstering consumer trust in green products and thereby promoting the overall evolution of the supply chain toward greening [40]. Contemporary research has extended game-theoretical applications to government-supported agri-food supply chain models, examining how tripartite relationships among producers, intermediaries, and regulatory bodies influence supply chain performance and sustainability outcomes [41]. However, these studies primarily focus on deterministic scenarios and static equilibrium analysis, leaving gaps in understanding dynamic evolutionary processes under stochastic market conditions. Recent developments in stochastic evolutionary game theory have been applied across supply chain contexts, including the supply chain [42]. In the context of supply chain finance credit markets, a nonlinear stochastic evolutionary game model was developed to analyze the dynamic interactions between small and medium-sized enterprises (SMEs) and financial institutions. By employing the fixed-point method, the researchers explored the conditions for mean-square exponential stability of the system, revealing that higher credit ratios from financial institutions, combined with stringent penalty mechanisms imposed by core enterprises, accelerate system stability, thereby offering practical guidance for mitigating credit risks [43]. In the realm of online supply chain finance, researchers have utilized a stochastic evolutionary game model to investigate the competition and cooperation dynamics between e-commerce enterprises and commercial banks. The findings indicate that high-penalty contracts substantially increase the likelihood of selecting cooperative strategies, with stochastic disturbance intensity, default penalties, and revenue-sharing proportions critically influencing the evolutionary process, thus providing a theoretical foundation for achieving mutually beneficial cooperation [44]. In the prefabricated building supply chain, a stochastic evolutionary game model involving four stakeholder groups was constructed, incorporating Gaussian white noise to simulate random perturbations and analyze carbon emission reduction strategies. The study demonstrated that emission benefits, costs, external environmental losses, and information sharing significantly shape participants' strategy choices, underscoring the critical role of supply chain management and cross-industry information-sharing platforms in promoting carbon emission reduction [45]. However, a significant research gap exists in applying stochastic evolutionary game methodology specifically to agricultural supply chains under environmental regulation and digital technology integration. Most researchers focus on deterministic evolutionary models or examine bilateral relationships in isolation, failing to capture the complex three-way interactions among government regulations, digital technology adoption, and farmer behavior under market uncertainty.

Researchers have examined the roles of digital technologies and environmental regulations in green agri-food supply chains from multiple perspectives. Regarding digital technologies, scholars have focused on technology types, application scenarios, and their contributions to improving supply chain efficiency and transparency. In terms of environmental regulations, researchers have concentrated on the incentive mechanisms of policy instruments and their impact on the overall greening of supply chains. Additionally, evolutionary game theory has been widely applied to analyze the dynamic decision-making processes of supply chain stakeholders. The researchers further integrate the reality of market uncertainty, constructing a stochastic evolutionary game model that accounts for bounded rationality markets, thereby providing advanced theoretical guidance.

Despite significant progress in existing research, several limitations remain: (1) Most studies rely on static analyses, lacking dynamic simulations and empirical validation of the long-term evolutionary paths of green supply chains. (2) The mechanisms through which environmental regulations drive the empowerment of green supply chains by digital technologies via tripartite game dynamics have yet to be systematically framed. (3) We incorporate decision-making under bounded rationality by agri-food supply chain stakeholders and the government in the context of market fluctuations, an aspect underexplored in evolutionary game research.

In summary, examining the roles of digital technologies and environmental regulations in green agri-food supply chains under conditions of market stochastic fluctuations and irrational decision-making is of significant importance. Digital technologies provide technical support for greening by enhancing supply chain transparency, efficiency, and sustainability, while environmental regulations drive stakeholders toward greening through policy incentives and constraints. Through this research, we aim not only to enrich the theoretical framework of green agri-food supply chains but also to provide practical guidance for policy formulation and technology adoption.

3. Model setting

3.1. Question descriptions

In the evolutionary process of green agri-food supply chains, the government, farmers, and wholesalers constitute three interrelated and dynamically interacting actors. As the institutional designer and environmental regulator, the government influences the transformation toward greening and digitalization by implementing subsidies, penalties, and regulatory policies. Farmers, as the primary producers of green agri-food products, choose between green and non-green production modes, with their decisions influenced by the high costs of green production, potential market premiums, and policy incentives. Wholesalers, serving as the central link in the midstream of the supply chain, decide whether to adopt digital technologies to enhance traceability and improve consumer trust in green products. While digital technology amplifies consumer green preferences and increases product value, it also entails significant upfront investment costs. In this study, digital empowerment refers to wholesalers' adoption of digital technologies (primarily blockchain and IoT) to enhance supply chain transparency, improve product traceability, and strengthen consumer trust in green agri-food products. This empowerment enables wholesalers to amplify consumer preferences for green products through verified information sharing and real-time monitoring capabilities. The government's regulatory intensity affects not only the income structure of farmers and wholesalers but also its own returns in terms of environmental improvement and public health benefits. The three actors have formed an interactive mechanism centered on policy guidance, market feedback, and technological choice, as illustrated in Figure 2. In this mechanism, the government influences the behavioral strategies of farmers and wholesalers through regulatory instruments, while the evolving strategies of farmers and wholesalers, in turn, affect the government's regulatory performance and social benefits, thus constituting a dynamically adjusting game system.

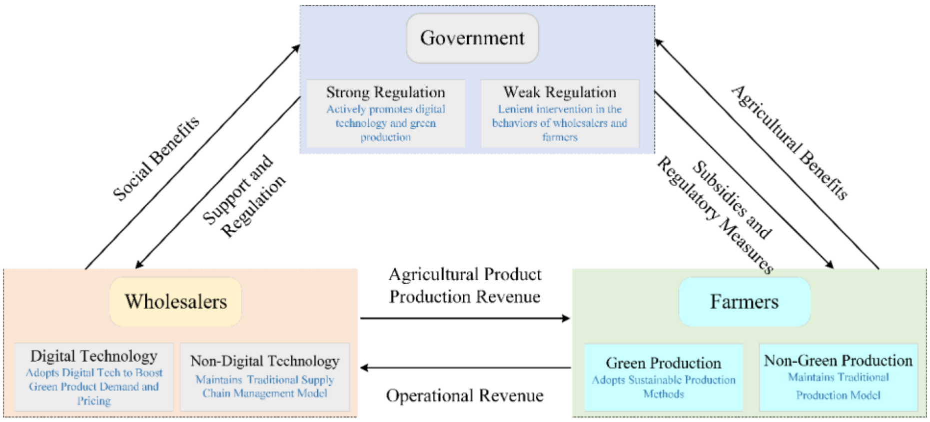

Figure 2. Game relationships among stakeholders in the green agri-food supply chain.

In this study, we establish a clear causal logic chain connecting environmental regulation, digital technology, and supply chain transformation. Environmental regulations create systematic incentive structures that fundamentally alter stakeholder behavior by modifying cost-benefit calculations and risk assessments. These regulatory mechanisms serve as the institutional foundation that drives behavioral change across the supply chain network.

Digital technologies function as enabling mechanisms that amplify regulatory effects through two primary channels: Enhanced supply chain transparency and increased consumer trust. When wholesalers adopt digital technologies such as blockchain and IoT systems, they create verifiable information flows that enable consumers to distinguish green and conventional products. This technological transparency transforms regulatory compliance from a cost burden into a market advantage, as verified green practices command premium prices and enhanced consumer loyalty.

The synergistic interaction between environmental regulations and digital technologies accelerates supply chain transformation through a three-way mechanism. Government regulations provide the institutional push by establishing clear incentives for green production and penalties for non-compliance. Digital technologies create market pull effects by enhancing consumer demand for verified green products and improving supply chain coordination efficiency. The evolutionary dynamics capture the adaptive responses of all stakeholders as they continuously adjust their strategies based on changing market conditions, regulatory pressures, and technological opportunities. This integrated framework explains how regulatory pressure and technological enablement work together to drive sustainable transformation, with each component reinforcing the others to create a self-sustaining green transformation process.

3.2. Model assumptions

Assumption 1. Farmers, wholesalers, and the government are bounded rational actors, each making strategic decisions based on utility maximization. Due to limited information about the strategies of others, their decisions evolve over time through learning and adaptation. x represents the probability that farmers choose green production, y represents the probability that wholesalers adopt digital technologies, and z represents the probability that the government implements stringent regulation.

Assumption 2. The total market demand is Q, and demand for green agri-food products is influenced by consumers' green preference, β. Green products carry a price premium, ΔP, over non-green products. Wholesalers adopting digital technologies enhance supply chain transparency and traceability, further amplifying consumer demand for green products. θ represents the amplification effect on consumer preference, θ, where $\theta > 1$.

Assumption 3. The cost of producing green agri-food products for farmers is C_g, which is higher than the cost of producing non-green products, C_l, i.e., $C_g > C_l$. The cost for wholesalers to adopt digital technologies is a one-time investment, C_d. When wholesalers adopt digital technologies, they increase consumer confidence in the green nature of agri-foods, resulting in a price ofP_{dg}. When wholesalers do not adopt digital technologies, the price for green products is P_g. For non-green products, the unified price set by wholesalers is P_n.

Assumption 4. The government incurs a fixed administrative cost, C_G, to implement stringent regulation. Under strong regulation, the government provides subsidies S_g for farmers' green production behaviors and imposes penalties F for non-green behaviors. The government also subsidizes wholesalers' adoption of digital technologies with S_d. When farmers engage in green production and wholesalers adopt digital technologies, the government's social benefit is W_{dg}. If either farmers or wholesalers independently engage in green production or digital technology use, the government's social benefits are W_g and W_d, respectively.

Table 1. Definitions of model parameters and variables.

Name	Definition
Q	Initial Total Market Demand
β	Consumer Preference for Green Products
P_l	Price of Non-Green agri-food Products Sold by Farmers
ΔP	Additional Revenue from Farmers Selling Green agri-food Products
C_l	Cost of Producing Non-Green agri-food Products by Farmers
C_g	Cost of Producing Green agri-food Products by Farmers
P_n	Price of Non-Green agri-food Products Sold by Wholesalers
P_g	Price of Green agri-food Products Sold by Wholesalers Without Digital Technology

Continued on next page

P_{dg}	Price of Green agri-food Products Sold by Wholesalers With Digital Technology
C_d	Cost of Adopting Digital Technology by Wholesalers
θ	Increase in Demand for Green agri-food Products After Wholesalers Adopt Digital Technology
S_g	Subsidy for Farmers Producing Green Products Under Stringent Government Regulation
S_d	Subsidy for Wholesalers Adopting Digital Technology Under Stringent Government Regulation
F	Penalty for Farmers Producing Non-Green Products Under Stringent Government Regulation
C_G	Cost of Stringent Government Regulation
W_{dg}	Social Benefits When Farmers Choose Green Production and Wholesalers Adopt Digital Technology
W_d	Social Benefits When Farmers Choose Green Production and Wholesalers Do Not Adopt Digital Technology
W_g	Social Benefits When Farmers Do Not Choose Green Production and Wholesalers Adopt Digital Technology

3.3. Construction of the tripartite evolutionary game model

Based on the model assumptions, the following payoff matrix is established (Table 2):

Table 2. Payoff matrix of the game.

				Government	
				Strong (z)	Weak ($1-z$)
Farmers	Green Production (x)	Wholesalers	Digital Technology (y)	$\theta\ \beta\ Q(P_l+\Delta\mathrm{P})+S_g-C_g$; $\theta\ \beta\ Q\left(P_{dg}-P_l-\Delta\mathrm{P}\right)+S_d-C_d$; $W_{dg}-S_g-S_d-C_G$	$\theta\ \beta\ Q(P_l+\Delta\mathrm{P})-C_g$; $\theta\ \beta\ Q\left(P_{dg}-P_l-\Delta\mathrm{P}\right)-C_d$; W_{dg}
			Non-Digital Technology ($1-y$)	$\beta\ Q(P_l+\Delta\mathrm{P})+S_g-C_g$; $\beta\ Q\left(P_g-P_l-\Delta\mathrm{P}\right)$; $W_g-S_g-C_G$	$\beta\ Q(P_l+\Delta\mathrm{P})-C_g$; $\beta\ Q\left(P_g-P_l-\Delta\mathrm{P}\right)$; W_g
	Non-Green Production ($1-x$)	Wholesalers	Digital Technology (y)	$\theta\ \beta\ QP_l-C_l-F$; $\theta\ \beta\ Q\ (P_n-P_l)+S_d-C_d$; $W_d+F-S_d-C_G$	$\theta\ \beta\ QP_l-C_l$; $\theta\ \beta\ Q\ (P_n-P_l)-C_d$; W_d
			Non-Digital Technology ($1-y$)	$\beta\ QP_l-C_l-F$; $\beta\ Q\ (P_n-P_l)$; $F-C_G$	$\beta\ QP_l-C_l$; $\beta\ Q\ (P_n-P_l)$; 0

(1) Farmers' perspective analysis

The payoff for farmers producing green agri-food products is denoted as, and the parameter names and their explanations are shown in Table 1.

$$
\begin{aligned}
\pi_{f1} = {} & yz\left(\theta\ \beta\ Q(P_l+\Delta\mathrm{P})+S_g-C_g\right)+y(1-z)\left(\theta\ \beta\ Q(P_l+\Delta\mathrm{P})-C_g\right)\pi_{f1} \\
& +(1-y)z\left(\beta\ Q(P_l+\Delta\mathrm{P})+S_g-C_g\right)+(1-y)(1-z)\left(\beta\ Q(P_l+\Delta\mathrm{P})-C_g\right) \\
& = \beta\ Q(P_l+\Delta\mathrm{P})+y(\theta-1)\beta\ Q(P_l+\Delta\mathrm{P})+zS_g-C_g
\end{aligned} \tag{1}
$$

The payoff for farmers producing non-green agri-food products is denoted as,

$$\pi_{f2} = yz(\theta\,\beta\,QP_l - C_l - F) + y(1-z)(\theta\,\beta\,QP_l - C_l) + (1-y)z(\beta\,QP_l - C_l - F) \\ +(1-y)(1-z)(\beta\,QP_l - C_l) = \beta\,QP_l + y(\theta-1)\beta\,QP_l - C_l - zF \tag{2}$$

Consequently, the expected average payoff for farmers is given by,

$$F(x) = \frac{dx}{dt} = x(1-x)\big(\pi_{f1} - \pi_{f2}\big) \\ = x(1-x)\big(\beta\,Q\Delta\mathrm{P} + \mathrm{y}(\theta-1)\beta\,Q\Delta\mathrm{P} + \mathrm{z}\big(S_g + F\big) + C_l - C_g\big). \tag{3}$$

(2) Wholesaler profit analysis

The payoff for wholesalers adopting digital technology is denoted as, and the parameter names and their explanations are shown in Table 1.

$$\pi_{w1} = xz\big(\theta\,\beta\,Q\,\big(P_{dg} - P_l - \Delta\mathrm{P}\big) + S_d - C_d\big) + x(1-z)\big(\theta\,\beta\,Q\,\big(P_{dg} - P_l - \Delta\mathrm{P}\big) - C_d\big) \\ +z(1-x)(\theta\,\beta\,Q\,(P_n - P_l) + S_d - C_d) + (1-x)(1-z)(\theta\,\beta\,Q\,(P_n - P_l) - C_d) \\ = \theta\,\beta\,Q\,\Big(x\big(P_{dg} - P_l - \Delta\mathrm{P}\big) + (1-x)(P_n - P_l)\Big) + zS_d - C_d. \tag{4}$$

The payoff for wholesalers not adopting digital technology is denoted as,

$$\pi_{w2} = xz\left(\beta\,Q\,\big(P_g - P_l - \Delta\mathrm{P}\big)\right) + x(1-z)\left(\beta\,Q\,\big(P_g - P_l - \Delta\mathrm{P}\big)\right) \\ +z(1-x)\big(\beta\,Q\,(P_n - P_l)\big) + (1-x)(1-z)\big(\beta\,Q\,(P_n - P_l)\big) \\ = \beta\,Q\,\Big(x\big(P_{dg} - P_l - \Delta\mathrm{P}\big) + (1-x)(P_n - P_l)\Big). \tag{5}$$

Consequently, the expected average payoff for wholesalers is given by,

$$F(y) = \frac{dy}{dt} = y(1-y)(\pi_{w1} - \pi_{w2}) \\ = y(1-y)\Big((\theta-1)\beta\,Q\,\Big(x\big(P_{dg} - P_l - \Delta\mathrm{P}\big) + (1-x)(P_n - P_l)\Big) + zS_d - C_d\Big). \tag{6}$$

(3) Government benefit analysis

The payoff for the government adopting stringent regulation is denoted as, and the parameter names and their explanations are shown in Table 1.

$$\pi_{G1} = xy\big(W_{dg} - S_g - S_d - C_G\big) + x(1-y)W_g + (1-x)y(W_d + F - S_d - C_G) \\ +(1-x)(1-y)(F - C_G). \tag{7}$$

The payoff for the government adopting weak regulation is denoted as,

$$\pi_{G2} = xyW_{dg} + x(1-y)W_g + (1-x)yW_d. \tag{8}$$

Consequently, the expected average payoff for the government is given by,

$$F(z) = \frac{dz}{dt} = z(1-z)(\pi_{G1} - \pi_{G2}) \\ = z(1-z)\big(-xy\big(S_g + C_G\big) - x(F - C_G) - yS_d + F - C_G\big). \tag{9}$$

3.4. Construction of the stochastic evolutionary game model

In reality, the strategic interactions among farmers, wholesalers, and the government in green agri-food supply chains are subject to significant uncertainties. First, the bounded rationality and psychological factors of the agents, such as emotional fluctuations and moral hazards, often lead to unexpected deviations in strategy selection. Second, changes in the macro environment, including economic fluctuations, policy adjustments, and market dynamics, profoundly influence agents' decision-making. Third, the intricate interplay of interests among agents tends to induce opportunistic behavior, further exacerbating the system's instability [38,39].

We adopt a stochastic evolutionary game model to capture the realities of agricultural supply chain decision-making under uncertainty. Unlike deterministic models that assume stable environments and perfect rationality, our stochastic approach incorporates random perturbations representing the inherent uncertainties in agricultural markets, including weather variability, commodity price fluctuations, policy implementation delays, and the bounded rationality of farmers, wholesalers, and government officials. The key advantage of this stochastic modeling is its enhanced realism: random terms capture unpredictable market shocks, psychological factors affecting stakeholder decisions, and the cumulative effects of small perturbations that can lead to different evolutionary outcomes than predicted by deterministic models. This approach enables for pathway diversity where identical initial conditions may result in different equilibria, convergence speed variations due to random market events, and temporary departures from deterministic trajectories that better reflect the non-linear responses observed in real agricultural supply chains facing unexpected disruptions. To effectively capture these external stochastic disturbances, we extend the replicator dynamics equations of the tripartite evolutionary game by incorporating Gaussian white noise [46], as detailed below:

$$dx(t) = \left(\beta\, Q\Delta \mathrm{P} + \mathrm{y}(\theta - 1)\beta\, Q\Delta \mathrm{P} + \mathrm{z}\left(S_g + F\right) + C_l - C_g\right)x(t)d(t) + \sigma x(t)dw(t), \tag{10}$$

$$y(t) = \left((\theta - 1)\beta Q\left(x\left(P_{dg} - P_l - \Delta \mathrm{P}\right) + (1 - x)(P_n - P_l)\right) + zS_d - C_d\right)y(t)d(t) + \sigma y(t)dw(t), \tag{11}$$

$$dz(t) = \left(-xy\left(S_g + C_G\right) - x(F - C_G) - yS_d + F - C_G\right)z(t)d(t) + \sigma z(t)dw(t). \tag{12}$$

Here, $w(t)$ represents a one-dimensional Brownian motion, which is a phenomenon of irregular random fluctuations and effectively reflects the impact of random disturbances on the game participants. $dw(t)$ is Gaussian white noise, and when $t > 0$ and step size $h > 0$, its increment $\Delta w(t) = w(t + h) - w(t)$ follows a normal distribution $N\left(0, \sqrt{h}\right)$. σ represents the intensity of the random disturbance.

4. Evolutionary stability analysis

4.1. Stability analysis of the tripartite evolutionary game model

Based on the payoff function of farmers derived in Section 3.3.1, it can be inferred that:

①When $y = \frac{C_g - \beta\, Q\Delta \mathrm{P} - \mathrm{z}\left(S_g + F\right) - C_l}{(\theta - 1)\beta\, Q\Delta \mathrm{P}}$, $F(x) \equiv 0$, it indicates that under this condition, the agricultural supply chain system is stable. Specifically, for any value of x, the farmer's green production strategy is stable, and the probability of strategy selection will not change over time.

②When $y \neq \frac{C_g-\beta\ Q\Delta\text{P}-\text{z}(S_g+F)-C_l}{(\theta-1)\beta\ Q\Delta\text{P}}$, two cases arise: Case 1: When $0 < y < \frac{C_g-\beta\ Q\Delta\text{P}-\text{z}(S_g+F)-C_l}{(\theta-1)\beta\ Q\Delta\text{P}}$, where, $F'(x)|_{x=0} < 0, F'(x)|_{x=1} > 0$. In this case, $x = 0$ is the stable evolution point, meaning that when the proportion of wholesalers choosing digital technology is lower than $\frac{C_g-\beta\ Q\Delta\text{P}-\text{z}(S_g+F)-C_l}{(\theta-1)\beta\ Q\Delta\text{P}}$, farmers will evolve to choose the production of non-green products. This occurs because when the probability of wholesalers adopting digital technology is low, they are unable to guide consumers' green preferences, which results in an inability to expand the demand for green agri-food products. Additionally, the price of green agri-food products sold by wholesalers will also be relatively low, which over time will cause all farmers to choose to produce non-green products. Case 2: When $\frac{C_g-\beta\ Q\Delta\text{P}-\text{z}(S_g+F)-C_l}{(\theta-1)\beta\ Q\Delta\text{P}} < y < 1$, where, $F'(x)|_{x=0} > 0, F'(x)|_{x=1} < 0$ In this case, $x = 1$ is the stable evolution point. When the proportion of wholesalers choosing digital technology exceeds $\frac{C_g-\beta\ Q\Delta\text{P}-\text{z}(S_g+F)-C_l}{(\theta-1)\beta\ Q\Delta\text{P}}$, farmers will evolve to choose the production of green agri-food products. This happens because when the probability of wholesalers adopting digital technology is high, consumers will have greater trust in the source of green agri-food products, increasing demand for these products. Consequently, farmers will evolve to choose the production of green agri-food products.

The strategy evolution phase diagram for farmers is shown in Figure 3(a).

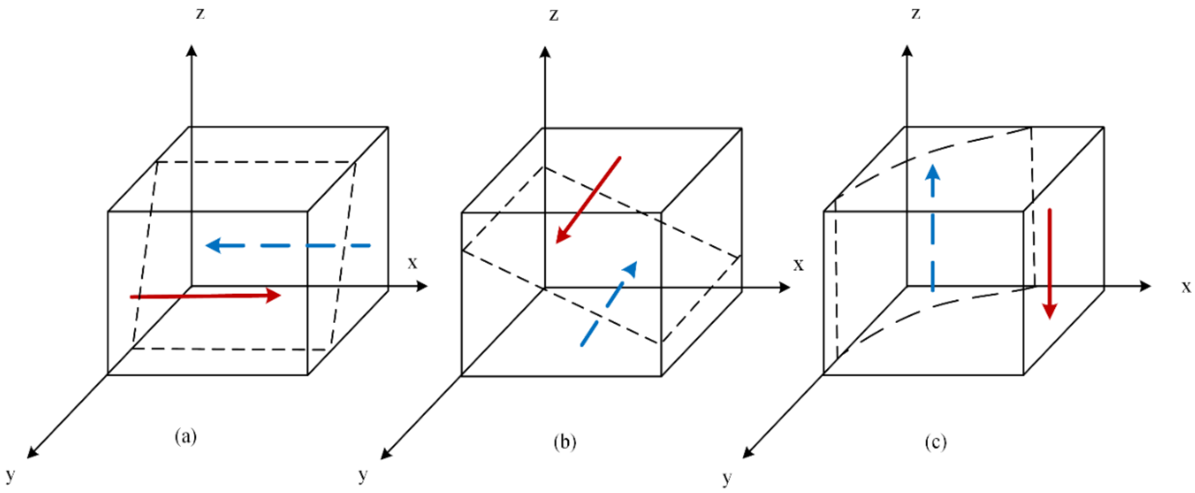

Figure 3. Phase diagram of the tripartite evolutionary game.

Based on the payoff function of wholesalers derived in Section 3.3.2, it can be inferred that,

①When $z = \frac{C_d-x(P_{dg}-P_l-\Delta\text{P})+(1-x)(P_n-P_l)}{S_d}$, $F(y) \equiv 0$, it indicates that under the decisions of wholesalers and the government, for any value of y, the agricultural supply chain system is stable. Specifically, for any proportion, the wholesalers' regulatory strategy is stable and the proportion of wholesalers' strategies will not change over time.

②When $z \neq \frac{C_d - x(P_{dg} - P_l - \Delta P) + (1-x)(P_n - P_l)}{S_d}$, two cases arise: Case 1: When $0 < z < \frac{C_d - x(P_{dg} - P_l - \Delta P) + (1-x)(P_n - P_l)}{S_d}$,where, $F'(y)|_{y=0} < 0, F'(y)|_{y=1} > 0$. In this case, $y = 0$ is the stable evolution point. When the proportion of strong government regulation is lower than $\frac{C_d - x(P_{dg} - P_l - \Delta P) + (1-x)(P_n - P_l)}{S_d}$, wholesalers will not choose digital technology. This is because the adoption of digital technology requires certain costs, and in the context of uncertain market demand, if the government's subsidy is weak, wholesalers will ultimately refrain from adopting digital technology. Case 2: When $\frac{C_d - x(P_{dg} - P_l - \Delta P) + (1-x)(P_n - P_l)}{S_d} < z < 1$,where, $F'(y)|_{y=0} > 0, F'(y)|_{y=1} < 0$. In this case, $y = 1$ is the stable evolution point. When the proportion of strong government regulation exceeds $\frac{C_d - x(P_{dg} - P_l - \Delta P) + (1-x)(P_n - P_l)}{S_d}$, wholesalers will choose the digital technology strategy. This is because strong government regulation not only provides direct subsidies for wholesalers to adopt digital technology but also encourages farmers to produce green agri-food products, which in turn motivates wholesalers to adopt digital technologies to better promote the sale of green agri-food products.

The strategy evolution phase diagram for wholesalers is shown in Figure 3(b).

Based on the government's profit function from Section 3.3.3, we have:

①When $x = \frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$, where, $F(z) \equiv 0$, it indicates that under this condition, for any value of z, the system is in a stable state. Specifically, at this point, the government's choice of regulatory strategy, regardless of the proportion, is stable, and the regulatory strategy proportion remains constant over time.

②When $x \neq \frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$, two cases arise. Case 1: When $0 < x < \frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$,where, $F'(z)|_{z=0} > 0, F'(z)|_{z=1} < 0$. In this case, $z = 1$ is the stable evolution point. When the proportion of farmers choosing green agri-food products is lower than $\frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$, the government will ultimately choose strong regulation. This is because the government aims to maximize overall social benefits, and green agri-food products are crucial for people's health and well-being. In the absence of self-organizing market forces, the government will implement strong regulation to encourage farmers to engage in green production. Case 2: When $x \neq \frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$,where $F'(z)|_{z=0} > 0, F'(z)|_{z=1} < 0$. In this case, $z = 0$ is the stable evolution point. When the proportion of farmers choosing green agri-food products exceeds $\frac{-yS_d + F - C_G}{y(S_g + C_G) + F - C_G}$, the government will choose weak regulation. This is because a self-organizing green agri-food product supply chain has already formed in the market, and in order to save regulatory costs, the government will withdraw from strong regulation.

The evolution phase diagram of the government's strategy is shown in Figure 3(c).

By setting $F(x) = 0, F(y) = 0, F(z) = 0$, we obtain the following 8 pure equilibrium points: $E_1(0,0,0), E_2(0,1,0), E_3(0,1,1), E_4(0,0,1), E_5(1,0,0), E_6(1,1,0), E_7(1,0,1), E_8(1,1,1)$. According to evolutionary game theory, these 8 pure equilibrium points are substituted into the Jacobian matrix for stability analysis. The system's Jacobian matrix is as follows:

$$J=\begin{bmatrix}\frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z}\\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z}\\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z}\end{bmatrix}$$

$$=\begin{bmatrix}(1-2x)A_1 & x(1-x)(\theta-1)\beta\, Q\Delta\mathrm{P} & x(1-x)(S_g+F)\\ y(1-y)((\theta-1)\beta\, Q(P_{dg}-P_l-\Delta\mathrm{P})-(P_n-P_l)) & (1-2\mathrm{y})A_2 & y(1-y)S_d\\ z(1-z)(-y(S_g+C_G)-(F-C_G)) & z(1-z)(-x(S_g+C_G)) & (1-2\mathrm{z})A_3\end{bmatrix}$$

$$A_1=\beta\, Q\Delta\mathrm{P}+\mathrm{y}(\theta-1)\beta\, Q\Delta\mathrm{P}+\mathrm{z}(S_g+F)+C_l-C_g$$

$$A_2=(\theta-1)\,\beta\, Q\left(x(P_{dg}-P_l-\Delta\mathrm{P})+(1-x)(P_n-P_l)\right)+zS_d-C_d$$

$$A_3=-xy(S_g+C_G)-x(F-C_G)-\ yS_d+\ F-C_G.$$

By substituting the eight equilibrium points into the Jacobian matrix, the results are shown in the table below.

According to system dynamics theory, a sufficient and necessary condition for the zero solution of a linear homogeneous constant-coefficient system to be asymptotically stable is that all eigenvalues of the constant-coefficient matrix are negative. In other words, for an ESS, the eigenvalues of the corresponding Jacobian matrix must all be non-positive.

Table 3. Eigenvalues of the Jacobian matrix.

	λ_1	λ_2	λ_3
$E_1(0,0,0)$	$\beta\, Q\Delta\mathrm{P}+C_l-C_g$	$(\theta-1)\beta\, Q(P_n-P_l)-C_d$	$F-C_G$
$E_2(0,1,0)$	$\theta\beta\, Q\Delta\mathrm{P}+C_l-C_g$	$-((\theta-1)\beta\, Q(P_n-P_l)-C_d)$	$-S_d+F-C_G$
$E_3(0,1,1)$	$\theta\beta\, Q\Delta\mathrm{P}+S_g+F+C_l-C_g$	$-((\theta-1)\beta\, Q(P_n-P_l)+S_d-C_d)$	S_d-F+C_G
$E_4(0,0,1)$	$\beta\, Q\Delta\mathrm{P}+S_g+F+C_l-C_g$	$(\theta-1)\beta\, Q(P_n-P_l)+S_d-C_d$	$-F+C_G$
$E_5(1,0,0)$	$-(\beta\, Q\Delta\mathrm{P}+C_l-C_g)$	$(\theta-1)\beta\, Q(P_{dg}-P_l-\Delta\mathrm{P})-C_d$	0
$E_6(1,1,0)$	$-(\theta\beta\, Q\Delta\mathrm{P}+C_l-C_g)$	$-((\theta-1)\beta\, Q(P_{dg}-P_l-\Delta\mathrm{P})-C_d)$	$-(S_g+C_G+S_d)$
$E_7(1,0,1)$	$-(\beta\, Q\Delta\mathrm{P}+S_g+F+C_l-C_g)$	$(\theta-1)\beta\, Q(P_{dg}-P_l-\Delta\mathrm{P})+S_d-C_d$	0
$E_8(1,1,1)$	$-(\theta\beta\, Q\Delta\mathrm{P}+S_g+F+C_l-C_g)$	$-((\theta-1)\beta\, Q(P_{dg}-P_l-\Delta\mathrm{P})$ $+S_d-C_d)$	$S_g+C_G+S_d$

The real parts of the eigenvalues of the Jacobian matrix determine the stability of each equilibrium point. When all eigenvalues have negative real parts, the equilibrium point is an ESS. If any eigenvalue has a positive real part, the equilibrium point may be a unstable or a saddle point. If any eigenvalue has a zero real part, the equilibrium point is non-hyperbolic. We focus on analyzing the conditions under which the equilibrium points $E_1(0,0,0)$, $E_4(0,0,1)$ and $E_6(1,1,0)$ achieve stability.

$E_1(0,0,0)$ represents the scenario in which farmers opt for non-green production, wholesalers select non-digital technologies, and the government implements weak regulation. Under the conditions where $\beta\, Q\Delta\mathrm{P}<C_g-C_l$, $(\theta-1)\beta\, Q(P_n-P_l)<C_d$, $F<C_G$, the three eigenvalues of the equilibrium point $E_1(0,0,0)$ are all negative, indicating that this point is an Evolutionarily Stable

Strategy (ESS). Specifically, when the additional profits from green agri-food products are less than the cost differential between producing green and non-green products, farmers will choose non-green production. Similarly, when the additional revenue generated from adopting digital technologies in the market is less than the cost of adopting such technologies, wholesalers will prefer non-digital options. Furthermore, when the government's penalty intensity is lower than the cost of implementing strong regulation, the government will choose weak regulation.

$E_4(0,0,1)$ represents the scenario in which farmers choose non-green production, wholesalers opt for non-digital technologies, and the government implements strong regulation. When $\beta\, Q\Delta\mathrm{P} + S_g + F < C_g - C_l$, $(\theta-1)\beta\, Q(P_n - P_l) + S_d < C_d$, and $C_G < F$, the three eigenvalues of the equilibrium point $E_4(0,0,1)$ are all negative, indicating that this point is an ESS. Specifically, when the additional profits from green agri-food products, along with subsidies and penalties, are less than the cost difference between producing green and non-green products, farmers will choose non-green production. Similarly, when the additional sales revenue from adopting digital technologies, along with subsidies, is less than the cost of adopting digital technologies, wholesalers will choose non-digital options. In this context, when the government's penalty intensity exceeds the cost of implementing strong regulation, the government will opt for strong regulation.

$E_6(1,1,0)$ represents the scenario in which farmers engage in green production, wholesalers adopt digital technologies, and the government implements weak regulation. When $\theta\beta\, Q\Delta\mathrm{P} > C_g - C_l$, $(\theta-1)\beta\, Q\left(P_{dg} - P_l - \Delta\mathrm{P}\right) > C_d$, $-\left(S_g + C_G + S_d\right) < 0$, the three eigenvalues of the equilibrium point $E_6(1,1,0)$ are all negative, indicating that this point is an ESS. Specifically, when the additional profits from green agri-food production exceed the cost difference between producing green and non-green products, farmers will choose to produce green agri-food products. Similarly, when the additional sales revenue from adopting digital technologies exceeds the cost of adopting such technologies, wholesalers will choose digital technologies, and in this case, the government will opt for weak regulation.

4.2. Equilibrium and stability analysis of the stochastic evolutionary game model

For the replicator dynamic Eqs (10)–(12) under random perturbations, when the game time is $t = 0$, and the initial conditions are $x(0) = 0, y(0) = 0, z(0) = 0$, the following holds:

$$\left(\beta\, Q\Delta\mathrm{P} + \mathrm{y}(\theta-1)\beta\, Q\Delta\mathrm{P} + \mathrm{z}\left(S_g + F\right) + C_l - C_g\right) \times 0 + \sigma x(t)dw(t) = 0, \tag{13}$$

$$\left((\theta-1)\beta\, Q\left(x\left(P_{dg} - P_l - \Delta\mathrm{P}\right) + (1-x)(P_n - P_l)\right) + zS_d - C_d\right) \times 0 + \sigma y(t)dw(t) = 0, \tag{14}$$

$$\left(-xy\left(S_g + C_G\right) - x(F - C_G) - yS_d + F - C_G\right) \times 0 + \sigma z(t)dw(t) = 0. \tag{15}$$

From the above three equations, it can be inferred that, $dw(t)|_{t=0} = w'(t)d(t)|_{t=0} = 0$, The zero solution exists for the equation, meaning that in the absence of external white noise, the zero solution serves as the equilibrium solution.

According to the stability criterion for Itô stochastic differential equations, under external perturbations, the zero solution is moment exponentially stable when the equation satisfies the following conditions:

$$\left(\beta\, Q\Delta\mathrm{P}+\mathrm{y}(\theta-1)\beta\, Q\Delta\mathrm{P}+\mathrm{z}\left(S_g+F\right)+C_l-C_g\right)x\leq-x, \tag{16}$$

$$\left((\theta-1)\beta\, Q\left(x\left(P_{dg}-P_l-\Delta\mathrm{P}\right)+(1-x)(P_n-P_l)\right)+zS_d-C_d\right)y\leq-y, \tag{17}$$

$$\left(-xy\left(S_g+C_G\right)-x(F-C_G)-\ yS_d+\ F-C_G\right)z\leq-z. \tag{18}$$

Simplifying the above expression, the condition that satisfies Eq (16) is:X_1: when $x\in(0,1]$, $\mathrm{y}\leq\frac{C_g-C_l-1-\mathrm{z}(S_g+F)-\beta\, Q\Delta\mathrm{P}}{(\theta-1)\beta\, Q\Delta\mathrm{P}}$. The condition that satisfies Eq (17) is: Y_1: when $y\in(0,1]$, $\mathrm{z}\leq\frac{x(P_n+\Delta\mathrm{P}-P_{dg})-P_n+P_l+C_d}{S_d}-\frac{1}{(\theta-1)\beta\, QS_d}$. The condition that satisfies Eq (18) is: Z_1: when $z\in(0,1]$,$-y\left(S_g+C_G\right)-(F-C_G)\leq0$, $\mathrm{x}\geq\frac{1+F-C_G-yS_d}{y(S_g+C_G)+(F-C_G)}$.

If the conditions in the above expressions hold simultaneously $X_1\cap Y_1\cap Z_1$, the strategies of the three parties will evolve to （0,0,0）.

Analytical solutions for nonlinear Itô stochastic differential equations are challenging to obtain. Therefore, drawing on related studies, the stochastic Taylor expansion is applied to Itô stochastic differential equations. We employ the Milstein method for numerical simulation. Based on the above principle, the corresponding Taylor expansions for farmers, wholesalers, and the government are derived as follows:

$$\begin{aligned}x(t_{n+1})=x(t_n)&+h(\beta\, Q\Delta\mathrm{P}+\mathrm{y}(\theta-1)\beta\, Q\Delta\mathrm{P}+\mathrm{z}\left(S_g+F\right)+C_l-C_g)x(t_n)\\&+\sigma x(t_n)\Delta w(t)+\frac{1}{2}[(\Delta w(t))^2-h]\sigma^2x(t_n)\\&+\frac{1}{2}h^2(\beta\, Q\Delta\mathrm{P}+\mathrm{y}(\theta-1)\beta\, Q\Delta\mathrm{P}+\mathrm{z}\left(S_g+F\right)+C_l-C_g)^2x(t_n)+R_1\end{aligned} \tag{19}$$

$$\begin{aligned}y(t_{n+1})=y(t_n)&+h((\theta-1)\,\beta\, Q\left(x\left(P_{dg}-P_l-\Delta\mathrm{P}\right)+(1-x)(P_n-P_l)\right)\\&+zS_d-C_d)y(t_n)+\sigma y(t_n)\Delta w(t)+\frac{1}{2}[(\Delta w(t))^2-h]\sigma^2y(t_n)\\&+\frac{1}{2}h^2((\theta-1)\,\beta\, Q\left(x\left(P_{dg}-P_l-\Delta\mathrm{P}\right)+(1-x)(P_n-P_l)\right)\\&+zS_d-C_d)^2y(t_n)+R_2\end{aligned} \tag{20}$$

$$\begin{aligned}z(t_{n+1})=z(t_n)&+h(-xy\left(S_g+C_G\right)-x(F-C_G)-\ yS_d+\ F-C_G)z(t_n)\\&+\sigma z(t_n)\Delta w(t)+\frac{1}{2}[(\Delta w(t))^2-h]\sigma^2z(t_n)\\&+\frac{1}{2}h^2(-xy\left(S_g+C_G\right)-x(F-C_G)-\ yS_d+\ F-C_G)^2z(t_n)+R_1\end{aligned} \tag{21}$$

5. Simulation analysis

To thoroughly investigate the dynamic game behavior and evolutionary stable strategies of farmers, wholesalers, and the government in the green transformation of the agricultural supply chain, we employ MATLAB 2023b for numerical simulation analysis. The research visualizes the strategy evolution paths of farmers, wholesalers, and the government under varying initial conditions, with a focus on analyzing the dynamic processes and convergence characteristics of the system stabilizing at equilibrium points $E_1(0,0,0)$, $E_4(0,0,1)$ and $E_6(1,1,0)$. Furthermore, we elucidate the impact of key parameters on evolutionary outcomes and conducts sensitivity analysis on core parameters to evaluate their effects on system stability and evolution speed.

5.1. Evolutionary path analysis

To investigate the evolutionary paths and stability of strategies adopted by farmers, wholesalers, and the government under varying incentive and cost conditions, we design three sets of initial parameter values, each corresponding to distinct economic scenarios, as shown in Table 4. In this section, we conduct comprehensive sensitivity analysis to examine how key parameters influence stakeholder strategy evolution. We design three distinct experimental scenarios representing different market development stages. Scenario 1 simulates early-stage markets characterized by high green production costs, limited consumer awareness, and minimal policy support, reflecting the initial challenges faced by emerging green agricultural markets. Scenario 2 represents transitional markets with increased regulatory pressure but insufficient incentive mechanisms, capturing the complexities of policy implementation during market transformation. Scenario 3 models mature markets with optimized cost structures, strong consumer demand for green products, and well-designed policy frameworks, illustrating the potential outcomes of successful green transformation initiatives. Each scenario enables systematic examination of parameter effects on system evolution and equilibrium outcomes, providing insights into the dynamic relationships between costs, incentives, and policy environments.

Table 4. Initial parameter values under different incentive and cost conditions.

	Q	β	ΔP	θ	C_l	C_g	P_l	P_n	P_{dg}	C_d	S_g	S_d	F	C_G
Parameter Set 1	10	0.2	0.1	1.2	2	5	3	3.5	4	2	0.5	0.5	0.5	1
Parameter Set 2	10	0.2	0.1	1.2	2	6	3	3.5	4	2.5	0.5	0.5	1.5	1
Parameter Set 3	10	0.5	0.2	1.5	2	3	3	4	6	2	1	1	1	1

Under the conditions of Parameter Set 1, we employ MATLAB 2023b for numerical simulations to analyze the strategy evolution paths of farmers, wholesalers, and the government in a scenario characterized by high green agri-food product production costs, low penalty intensity, and low incentive levels. The dynamic evolutionary trajectories of the system, as illustrated in Figure 2, demonstrate that, starting from various initial conditions, the system ultimately converges to the equilibrium point $E_1(0,0,0)$, where farmers opt for non-green production, wholesalers choose non-digital technology, and the government adopts weak regulation. To further validate the system's evolutionary behavior under specific initial conditions, we select a set of initial probabilities ($x = 0.5$, $y = 0.5$ and $z = 0.5$) for the participants and conducts simulations. The results, as shown in Figure 3, depict the evolutionary trends of the three parties' strategies over time and their convergence characteristics.

In Figure 4, multiple colored trajectory lines, starting from different initial points, all converge to the equilibrium point E_1, indicating that the system stabilizes at a state where farmers choose non-green production, wholesalers opt for non-digital technology, and the government adopts weak regulation. This aligns with the characteristics of Parameter Set 1: High green production costs make green practices economically unattractive, while low penalties and subsidies fail to incentivize farmers and wholesalers to adopt green production or digital technology. The government, with penalty costs lower than regulatory expenses, selects weak regulation. The rapid decline of trajectories reflects the suppressive effect of high costs and low returns on strategy choices, demonstrating that in a market lacking effective incentives and penalties, the agricultural supply chain struggles to achieve green transformation and stabilizes in a traditional mode. Figure 5 shows the probability evolution of the three parties' strategies with initial probabilities (0.5,0.5,0.5), consistent with Figure 4.

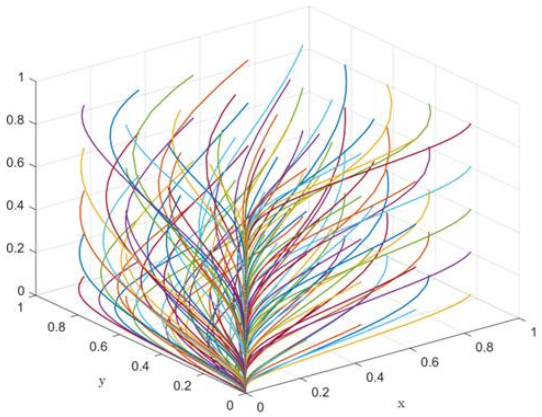

Figure 4. Evolution of stakeholders under parameter Set 1.

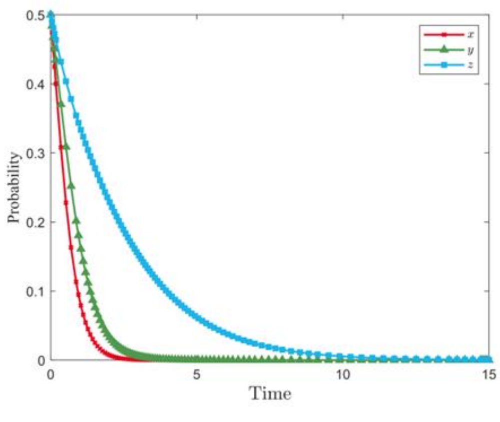

Figure 5. Probability evolution analysis for parameter Set 1.

Parameter Set 2 represents a scenario with high green agri-food product production costs, high penalty intensity, and low incentive levels. Figure 6 illustrates the dynamic evolutionary trajectories under Parameter Set 2, while Figure 7 depicts the strategy evolution process with initial probabilities of (0.5,0.5,0.5).

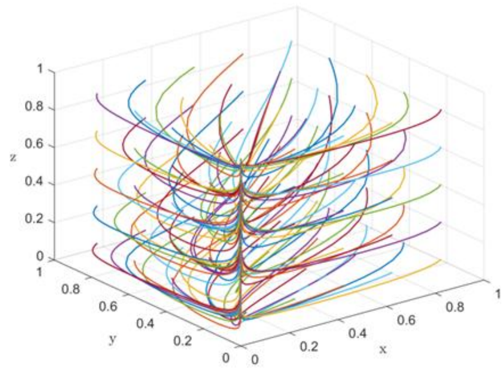

Figure 6. Evolution of stakeholders under parameter set 2.

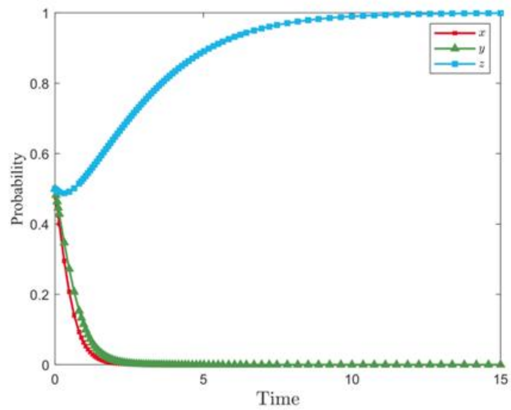

Figure 7. Probability evolution under parameter set 2.

Figure 6 demonstrates that the system stabilizes at the equilibrium point (0,0,1), where farmers choose non-green production, wholesalers opt for non-digital technology, and the government adopts strong regulation. This aligns with the characteristics of Parameter Set 2: high green production and digital technology costs, coupled with low returns and subsidies, suppress the adoption of green production and digital technology, while the government, driven by high penalty intensity, favors strong regulation, indicating that stringent regulation fails to promote the green transformation of the agricultural supply chain. Figure 7 illustrates the probability evolution of the three parties' strategies with initial probabilities (0.5,0.5,0.5). Despite an increased probability of the government choosing strong regulation, the high costs lead to outcomes consistent with Figure 6.

Parameter Set 3 represents a scenario with low green agri-food product production costs, moderate penalty intensity, and moderate incentive levels. Figure 8 depicts the dynamic evolutionary trajectories under Parameter Set 3, while Figure 9 illustrates the strategy evolution process with initial probabilities of (0.5,0.5,0.5).

Figure 8 demonstrates that the system stabilizes at a state where farmers choose green production, wholesalers adopt digital technology, and the government opts for weak regulation. This aligns with the characteristics of Parameter Set 3: low green production costs and high returns make green production more attractive, moderate incentives encourage wholesalers to adopt digital technology, and the government, due to the market's spontaneous green transformation, tends toward weak regulation. The trajectories in Figure 9 indicate that low costs and moderate incentives initially drive wholesalers to adopt digital technology, subsequently promoting the green transformation of agri-foodion.

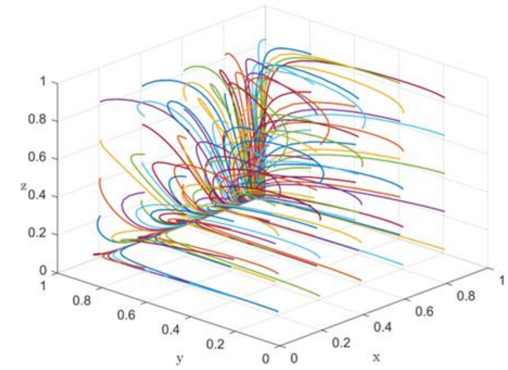

Figure 8. Evolution of stakeholders under parameter set 3.

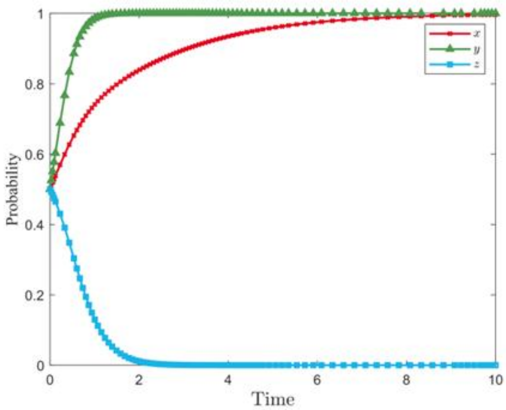

Figure 9. Probability evolution under parameter set 3.

Furthermore, considering external perturbations, we simulate the impact of initial strategies on evolutionary paths, with results shown in Figure 10.

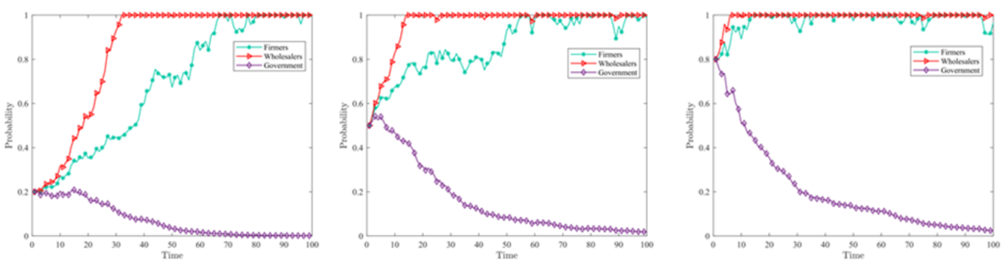

Figure 10. Impact of initial values on the dynamic evolutionary paths of the three parties under stochastic evolutionary game.

Figure 10 reveals the significant impact of the initial strategy probabilities of the three parties on the time required to reach game equilibrium. As the initial strategy probabilities of farmers, wholesalers, and the government increase from (0.2, 0.2, 0.2) to (0.8, 0.8, 0.8), the time required for farmers' strategies to converge to the equilibrium point is significantly reduced, from approximately 70 cycles to 15 cycles. However, influenced by external uncertainties and farmers' psychological factors, farmers' strategies still exhibit some fluctuations during the convergence process, particularly when the government gradually withdraws from strong regulation. The equilibrium time for wholesalers is similarly shortened, with minimal strategy fluctuations post-convergence, indicating that, due to the high costs of switching operational models, wholesalers tend to maintain the stability of their digital technology adoption strategy after making the choice.

5.2. Parameter sensitivity analysis

In this section, we examine the impact of parameters related to farmers, wholesalers, and the government on their strategy choices, including the cost of producing green agri-food products by farmers (C_g), additional revenue from selling green agri-food products (ΔP), the cost of adopting digital technology by wholesalers (C_d), the increase in demand for green agri-food products after wholesalers adopt digital technology (θ), the cost of stringent government regulation (C_G), and the penalty for farmers producing non-green products under stringent regulation (F). Through simulation analysis, these parameters reveal how they influence the strategic choices of stakeholders and the dynamic evolution of the green transformation in agri-food supply chains.

(1) Farmer parameter analysis

To investigate the impact of farmer-related parameters on the evolution of tripartite strategies, we conduct a simulation analysis using MATLAB under parameter set 3 to examine the effects of changes in green production costs and additional benefits of green products on system behavior. The results are presented in Figures 11–14.

The numerical simulation results from Figures 11 and 12 demonstrate that decreasing costs of green agri-food production accelerate the system's evolutionary trajectory, converging to the equilibrium (1,1,0), where farmers adopt green production, wholesalers implement digital technologies, and the government employs minimal regulation. Specifically, lower green production costs enhance farmers' economic incentives, reducing expenses and promoting green transitions for both farmers and wholesalers. Cost advantages and market premiums drive farmers' participation in green production, while wholesalers adopt digital technologies to boost product competitiveness. Enhanced supply chain transparency via digital technologies increases consumer trust in green products, stimulating demand. Consequently, the government can reduce regulatory intensity, minimizing administrative costs. Conversely, rising green production costs diminish farmers' incentives, resulting in limited strategic shifts despite sustained wholesaler adoption of digital technologies. The government maintains low regulatory intensity to avoid disrupting market-driven green transitions. This aligns with European organic farming experiences, where government subsidies and technical support to reduce green production costs led to significantly increased farmer adoption rates.

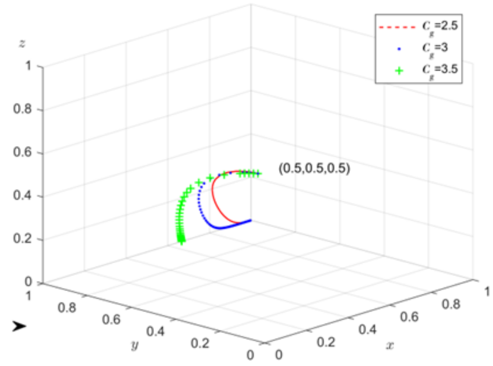

Figure 11. The impact of C_g on the behavioral evolution of the three stakeholders.

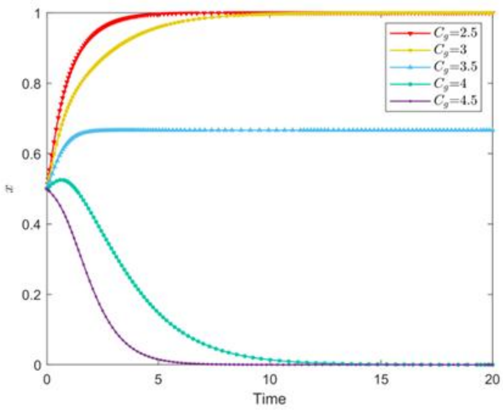

Figure 12. The impact of C_g on the behavioral evolution of farmers.

The simulation results from Figures 13 and 14 indicate that an increase in the additional benefits of green products leads to rapid convergence of the system's evolutionary trajectory to the equilibrium point (1,1,0), where farmers adopt green production, wholesalers implement digital technologies, and the government opts for light regulation. This suggests that higher market premiums for green agri-food products significantly enhance farmers' economic returns, incentivizing greater adoption of green production practices. Concurrently, rising market demand for green products prompts wholesalers to leverage digital technologies to improve supply chain transparency and product traceability, thereby boosting market trust and demand for green products. In this market-driven green transition, the government progressively reduces regulatory intensity, adopting light regulation policies to lower administrative costs and foster innovation and sustainable development. However, when the additional benefits of green products are zero, farmers evolve toward non-green production.

Under a randomly perturbed market, the additional benefits of green products exert an even stronger influence on farmers' decisions, as shown in Figure 15.

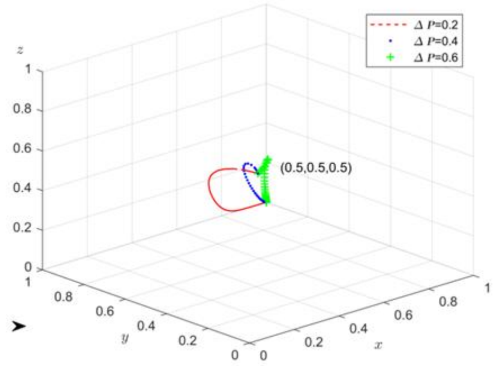

Figure 13. The impact of ΔP on the behavioral evolution of the three stakeholders.

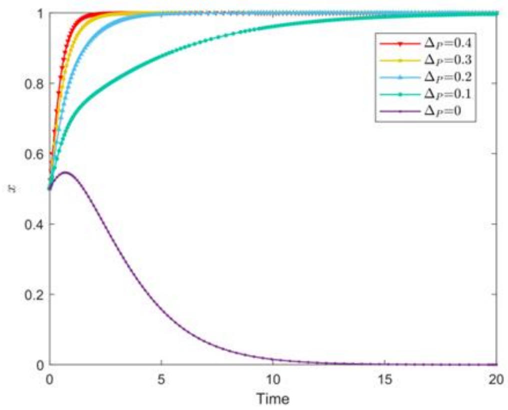

Figure 14. The impact of ΔP on the behavioral evolution of farmers.

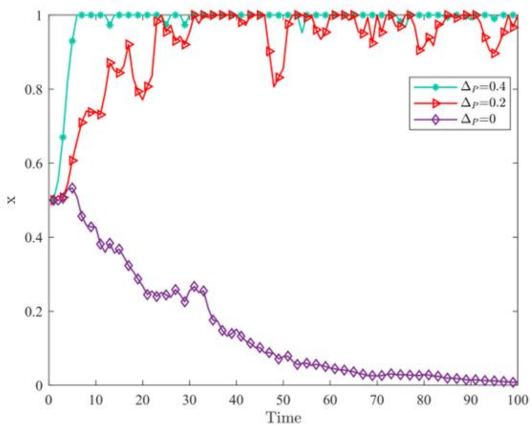

Figure 15. Impact of additional benefits of green agri-food products on farmers under stochastic evolutionary game.

The simulation results in Figure 15 reveal that when green agri-food products yield no additional market benefits, farmers gradually shift toward producing conventional agri-foods. This indicates that, in the absence of significant economic returns from green products, farmers typically opt for conventional production due to its relatively lower costs and stable market demand. In such scenarios, farmers tend to abandon green production to maximize short-term economic gains. Without additional market incentives, farmers naturally revert to a more conservative production mode.

However, when the additional benefits of green products increase to 0.4, farmers' choices rapidly converge and stabilize toward sustained green production. This suggests that higher market premiums for green products significantly enhance farmers' economic returns, incentivizing them to persist with green production despite market uncertainties. The elevated additional benefits enable farmers to recognize the long-term advantages of green production, leading to stable adoption and promoting a more efficient and sustainable green agri-food supply chain.

At an additional benefit level of 0.2, farmers' choices exhibit significant volatility. This fluctuation indicates that a lower premium for green products creates uncertainty in farmers' decisions between green and conventional production. At this critical threshold, farmers may oscillate between green and non-green production due to differences in short-term economic outcomes, resulting in an unstable decision-making process. Market uncertainties and farmers' bounded rationality exacerbate their decision-making challenges and strategic fluctuations at this benefit level. This reflects the reality of organic food and green certification markets, where appropriate price premiums are key drivers for farmers' transition to green production.

We compare Figure 15 with the deterministic counterparts shown in Figures 13 and 14. The deterministic models (Figures 13–14) predict smooth, monotonic convergence to equilibrium states, where farmers' strategies evolve predictably based solely on additional green product benefits. In contrast, the stochastic model (Figure 15) reveals significant strategy fluctuations, particularly at intermediate benefit levels ($\Delta P = 0.2$), where farmers oscillate between green and non-green production due to market uncertainties and bounded rationality. This comparison demonstrates that deterministic models may overestimate the stability of green transformation, while stochastic modeling captures the realistic volatility that policymakers must address. The stochastic approach shows that even with moderate green premiums, market uncertainties can create decision-making challenges that require additional policy support mechanisms to ensure stable green adoption.

(2) Wholesaler parameter analysis

To examine the impact of wholesaler-related parameters on the evolution of tripartite strategies, we conduct a simulation analysis using MATLAB under parameter set 3 to assess the effects of digital technology on enhancing demand for green agri-food products and the influence of changes in digital technology adoption on system behavior. The results are presented in Figures 16–19.

The simulation results from Figures 16 and 17 demonstrate that, starting from the initial point (0.5, 0.5, 0.5), when digital technology significantly enhances demand for green agri-food products, wholesalers rapidly adopt digital technologies, ultimately driving farmers to choose green production. As wholesalers implement digital technologies, consumer demand for green products is effectively boosted, leading farmers to increase their proportion of green production. The system stabilizes at the equilibrium point (1,1,0), where farmers adopt green production, wholesalers utilize digital technologies, and the government opts for light regulation. Conversely, when the impact of digital technology on demand is minimal, wholesalers cease to adopt digital technologies. However, under other conditions of parameter set 3, farmers choose to produce green agri-food products. The application of digital technologies in the supply chain, particularly blockchain and IoT, significantly enhances transparency and strengthens consumer trust in green products. When digital technology substantially increases demand, wholesalers' adoption of these technologies not only improves product market competitiveness but also amplifies demand for green products. This heightened demand further incentivizes farmers to adopt green production, as the market premium and enhanced consumer trust provide better economic returns. By leveraging digital technologies, wholesalers can optimize the supply chain, reduce costs, and improve product quality, thereby promoting the market expansion of green products. This guides farmers toward green production, creating a virtuous cycle. This corresponds to the application effects of blockchain traceability systems in the food industry, where digital technologies indeed enhance consumer trust and purchasing willingness for green products.

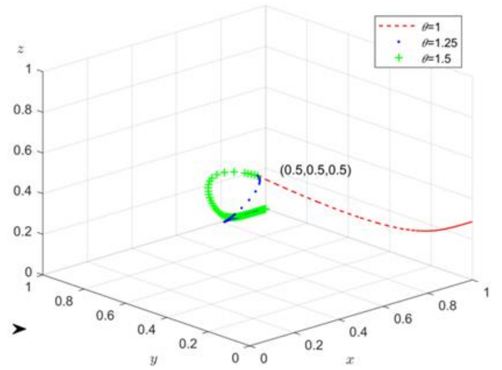

Figure 16. The impact of θ on the behavioral evolution of the three stakeholders.

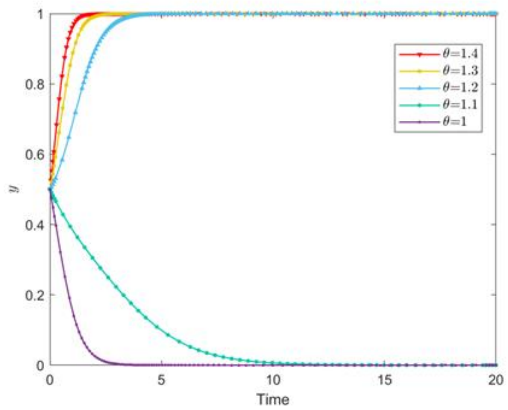

Figure 17. The impact of θ on the behavioral evolution of wholesales.

The simulation results from Figures 18 and 19 indicate that, at lower digital technology adoption costs, wholesalers rapidly adopt digital technologies, leading to swift system stabilization. Low costs enable wholesalers to quickly realize returns, including enhanced supply chain efficiency, increased product transparency, and greater consumer trust in green agri-food products. As digital technology adoption boosts demand for green products, it drives farmers to adopt green production, stabilizing the system in a state of concurrent green production and digital technology use. At moderate adoption costs, wholesalers passively adopt digital technologies only when farmers have already implemented green production. However, at high costs, wholesalers opt against digital technology, maintaining traditional supply chain management. This is because moderate costs position digital technology as neither widely affordable nor prohibitively advanced. When farmers adopt green production, creating value-added products, the realization of this value heavily depends on supply chain transparency. Without digital traceability, wholesalers cannot verify the carbon footprint advantage to downstream markets, losing premium pricing opportunities, thus necessitating digital technologies to establish a trusted "farm-to-table" linkage. This aligns with the actual situation of agricultural digital transformation, where declining technology costs are important drivers for enterprise adoption of digital technologies.

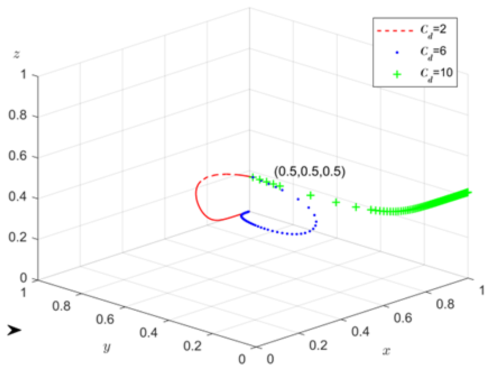

Figure 18. The impact of C_d on the behavioral evolution of the three stakeholders.

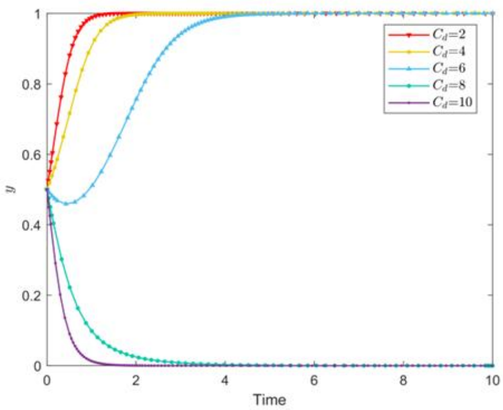

Figure 19. The impact of C_d on the behavioral evolution of wholesales.

The simulation results from Figure 20 indicate that when digital technology fails to significantly enhance market demand for green agri-food products, wholesalers gradually abandon its adoption. This occurs when digital technology does not effectively stimulate consumer demand for green products or when market demand for such products remains low. In such cases, wholesalers assess that the market returns from digital technology are insufficient to offset its high costs, leading them to reduce or cease investment in digital technology and revert to traditional supply chain management. However, as digital technology's role in boosting demand for green products becomes more evident, wholesalers accelerate its adoption. When consumer demand for green products grows, and digital technology enhances supply chain efficiency, product traceability, and market trust, the return on investment becomes clearer, significantly increasing the speed of adoption and reducing strategy volatility. This suggests that as digital technology drives higher market demand and efficiency, wholesalers' decisions stabilize, promoting a system state of sustained green production and digital transformation. This reflects consumers' growing demand for food safety and traceability, with digital technologies playing an important role in enhancing product transparency.

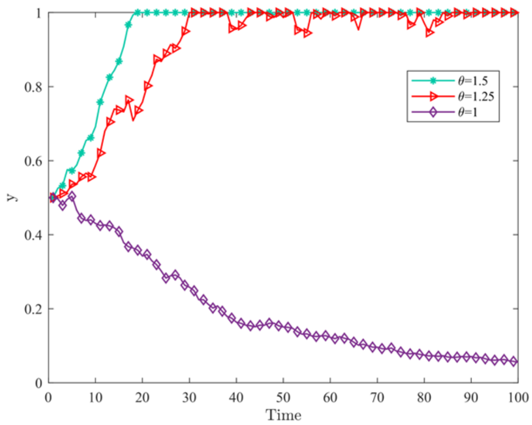

Figure 20. Impact of digital technology on green agri-food product demand (θ) on wholesalers.

Comparing Figure 20 with the baseline scenarios in Figures 16 and 17 illustrates the critical role of digital technology in supply chain transformation. The baseline models (Figures 16 and 17) show that without considering market uncertainties, digital technology adoption follows predictable patterns based on demand amplification effects (θ) and cost considerations. However, Figure 20 reveals that under stochastic conditions, wholesalers' digital adoption decisions become more sensitive to market volatility, with adoption rates fluctuating significantly when demand enhancement effects are marginal ($\theta < 1.3$). This comparison underscores the importance of incorporating both digital empowerment and stochastic elements in policy design, as deterministic models may underestimate the challenges of technology adoption in uncertain market environments. The stochastic analysis provides more realistic guidance for setting appropriate subsidies and market conditions necessary to ensure stable digital technology adoption in agricultural supply chains.

(3) Government parameter analysis

To investigate the impact of government-related parameters on the evolution of tripartite strategies, we conduct a simulation analysis using MATLAB under parameter set 3 to assess the effects of changes in government regulatory costs and penalties on system behavior. The results are presented in Figures 21–24.

As shown in Figures 21 and 22, when government regulatory costs are low, the system rapidly converges to the stable state (1,1,0), where wholesalers adopt digital technologies and farmers produce green agri-food products. Low regulatory costs enable the government to effectively promote green agriculture and digital transformation through policy incentives while minimizing administrative expenses, thereby accelerating the greening of the supply chain. Wholesalers quickly adopt digital technologies, enhancing supply chain efficiency, while farmers gain greater returns from green production, leading to rapid system stabilization. However, when regulatory costs are moderate, the system's evolutionary speed slows, indicating that government efforts to drive transformation face cost and policy constraints, resulting in slower adoption of green production and digital technologies. Although the government can provide some incentives, its policy effectiveness is limited, leading to slower system development. When regulatory costs are high, wholesalers often abandon digital technology adoption due to increased operational burdens. Moreover, despite a higher likelihood of farmers choosing green production, the government, facing high regulatory costs, opts for lighter regulation to reduce administrative burdens.

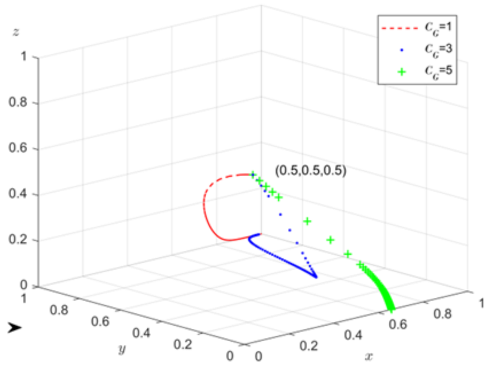

Figure 21. The impact of C_G on the behavioral evolution of the three stakeholders.

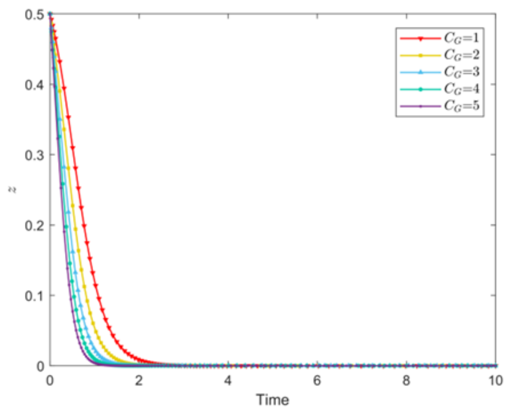

Figure 22. The impact of C_G on the behavioral evolution of government.

The results from Figures 23 and 24 indicate that as penalty amounts increase, the government increasingly adopts stringent regulatory strategies to promote the green transformation of farmers and wholesalers through strict enforcement measures. Higher penalties effectively constrain non-compliant behaviors, compelling farmers and wholesalers to adopt green production and digital technologies. However, as farmers progressively shift to green production and wholesalers begin adopting digital technologies, the market and supply chain gradually transition toward green and digitalized practices, rendering stringent government regulation less necessary. Once green production and digital technology adoption reach a certain threshold, the market develops a self-sustaining green transformation mechanism. Consequently, the government shifts from stringent regulation to a more flexible and lenient regulatory approach. This reflects the implementation effects of environmental regulatory policies, where moderate penalties can promote green transformation, but excessive penalties may cause market resistance.

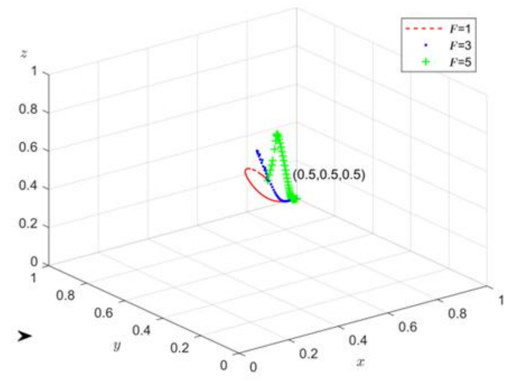

Figure 23. The impact of F on the behavioral evolution of the three stakeholders.

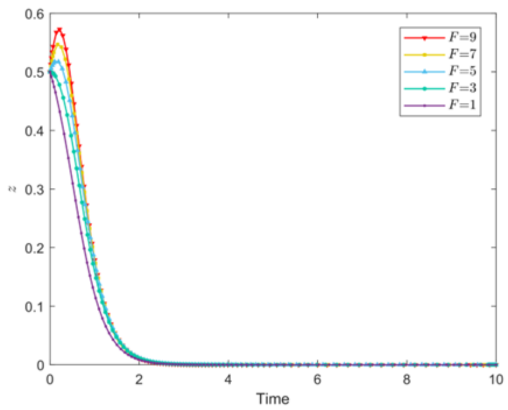

Figure 24. The impact of F on the behavioral evolution of government.

5.3. Case study: JD.com's free-range chicken project

To validate the effectiveness of the proposed research model, we select the "Running Chicken" poverty alleviation project initiated by JD Group in 2016 in Wuyi County, Hebei Province, as an empirical case study. In 2018, the project introduced blockchain technology, establishing an agricultural product supply chain system that integrates green production, digital traceability, and government poverty alleviation efforts, providing an ideal analytical sample for this study[a]. The local conventional broiler breeding cost in Wuyi County is approximately 25–35 CNY per chicken, whereas the JD "Running Chicken" project mandates a free-range breeding period of no less than 160 days, resulting in a breeding cost of 80–100 CNY per chicken, representing a cost increase of approximately 200–300%[b]. Price data demonstrate the significant impact of blockchain technology

[a] http://rmfp.people.com.cn/n1/2018/0626/c406725-30085395.html
[b] https://news.qq.com/rain/a/20201027A065IH00

on product premiums. Prior to the introduction of blockchain technology in 2016–2017, the purchase price of "Running Chicken" ranged from 98–128 CNY per chicken, compared to 35–45 CNY for conventional broilers, yielding a premium rate of approximately 180–200%. After implementing blockchain traceability in 2018, the retail price on the JD platform increased to 168 CNY per chicken, achieving a premium of 300–400% over conventional products[c]. According to media reports and industry analysis, sales data exhibited substantial growth, confirming the amplifying effect of digital technology on demand.

Based on the actual operational data of the JD Free-Range Chicken Project, we calibrate all parameters using the retail price of blockchain-certified products (168 CNY per chicken) as the benchmark (normalized to 10). Production cost parameters indicate that conventional breeding costs are $C_l = 1.79$ (30 CNY per chicken), while free-range chicken costs are $C_g = 5.36$ (90 CNY per chicken), reflecting a 200% cost increase due to the 160-day free-range period. In the pricing system, conventional products transition from a farmer price of $P_l = 2.38$ (40 CNY per chicken) to a wholesale price of $P_n = 2.98$ (50 CNY per chicken), whereas free-range chickens achieve a value increase from a retail price of $P_g = 6.55$ (without blockchain, 110 CNY per chicken) to $P_{dg} = 10$ (with blockchain, 168 CNY per chicken), resulting in a farmer-end premium of $\Delta P = 4.17$. Technical and policy parameters include: blockchain cost $C_d = 0.30$ (5 CNY per chicken), government breeding subsidy $S_g = 0.3$ (5 CNY per chicken), technology subsidy $S_d = 0.6$ (approximately 10 CNY per chicken), environmental violation penalty $F = 1.19$ (20 CNY per chicken), and government regulatory cost $C_G = 0.89$ (approximately 15 CNY per chicken). Market response parameters, derived from actual operational data, are set as follows: Consumer green preference $\beta = 0.45$ (based on a 45% scanning rate), demand amplification coefficient $\theta = 3.5$, and total market demand Q=10. This parameter system not only reflects the actual characteristics of the Chinese agricultural product supply chain but also provides a reliable empirical foundation for the evolutionary game model.

Based on the above data, we simulate the effects of ΔP and θ under a stochastic evolutionary game, with the results presented as follows:

Figure 25 illustrates the decisive impact of price premiums on the evolution of farmers' green production strategies. When ΔP = 4.17, the probability of farmers adopting green production converges rapidly to 100% within 10-time units, corroborating the actual evolutionary trajectory observed in the JD project, where farmer participation increased from 10% to 80%. When the premium decreases to ΔP = 2.0, the system's convergence speed significantly slows and exhibits fluctuations, requiring 30-time units to stabilize. At ΔP = 0, even with government subsidies, the probability of green production continues to decline to 20%, indicating that the absence of market incentives leads to the failure of green transformation. The simulation results reveal a critical threshold for price premiums (approximately 2.0–2.5), below which green transformation becomes unsustainable, providing a quantitative basis for policymaking: when market premiums are insufficient, governments must ensure reasonable returns for farmers through subsidies or other measures to maintain the sustainability of green transformation in the agricultural product supply chain.

Figure 26 elucidates the critical influence of the demand amplification effect of digital technology on wholesalers' decisions to adopt such technologies. When $\theta = 3.5$, the probability of wholesalers adopting digital technology converges rapidly to 100% within 20-time units, reflecting

[c] https://m.21jingji.com/article/20170523/f8b15bfc0be4e3295af8679a84c7d980.html

their rational choice under a strong demand amplification effect. At $\theta = 2$, the system's evolution exhibits significant uncertainty: the adoption rate slowly increases to approximately 95%, accompanied by persistent fluctuations, requiring 60-time units to stabilize, which highlights the investment dilemma faced by wholesalers under a moderate technological effect. When $\theta = 1$, the adoption rate steadily declines to around 25%, indicating that, in the absence of demand incentives, rational wholesalers gradually abandon digital technology investments. These results validate a key factor in the success of the JD project: blockchain technology significantly amplifies demand ($\theta = 3.5$) by enhancing consumer trust, thereby yielding clear economic returns on technology investments. The simulation reveals a critical threshold of $\theta \approx 1.5 - 2.0$, below which digital transformation cannot occur spontaneously, necessitating government interventions such as technology subsidies to lower adoption barriers or market cultivation to enhance technological effects.

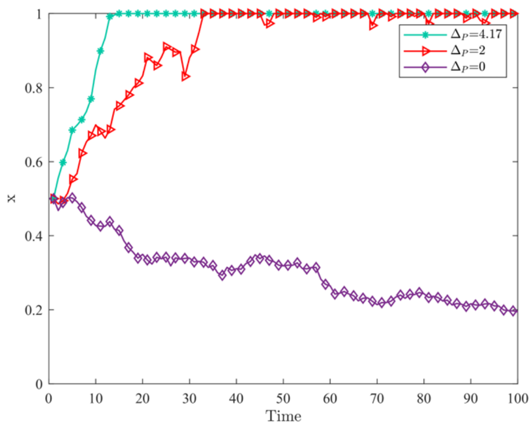

Figure 25. Impact of additional benefits of green agri-food products.

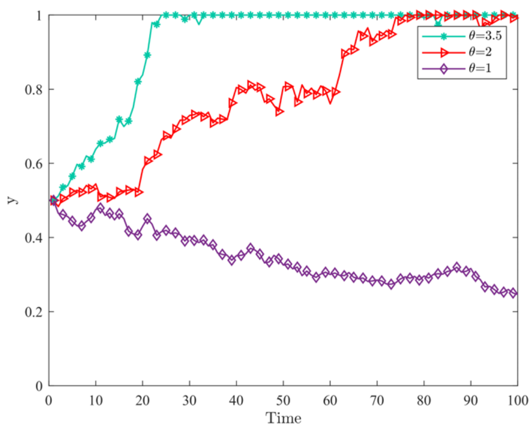

Figure 26. Impact of digital technology on green agri-food product demand on wholesalers.

6. Conclusions and recommendations

This study makes significant theoretical and methodological contributions to green supply chain management. First, we develop the first stochastic tripartite evolutionary game model that integrates environmental regulation and digital empowerment effects, advancing beyond existing deterministic bilateral models. Second, our research quantifies the synergistic mechanisms between policy interventions and technological adoption under market uncertainties, providing a robust analytical framework for sustainable agricultural transformation. Third, the parameter sensitivity analysis reveals critical thresholds for policy effectiveness, offering evidence-based guidance for optimal subsidy design and regulatory timing.

(1) We unveil the complex pathways through which agricultural supply chains evolve toward sustainable equilibria under market uncertainty, identifying multiple equilibrium states whose transitions depend on the interplay between blockchain transparency and regulatory incentives. By modeling market uncertainty as stochastic perturbations, we demonstrate how these disturbances influence the stability and trajectory of strategic choices, revealing a nonlinear feedback mechanism whereby technology adoption amplifies regulatory impacts. The empirical analysis of the JD Free-Range Chicken Project validates this theoretical framework—when the demand amplification coefficient reaches 3.5 and the price premium is 4.17, the system rapidly converges to a green equilibrium as predicted by the model, with farmer participation soaring from 10% to 80% within three years, confirming the mechanism of multiple equilibrium transitions under stochastic perturbations.

(2) Through large-scale numerical simulations, we quantify the temporal dynamics of convergence to sustainable equilibria, identifying combinations of technology adoption and regulatory policies that significantly accelerate the transition process. The analysis shows that digital technology-enhanced transparency, combined with precisely calibrated regulatory measures, can reduce the time to reach a stable sustainable state by 30%. This finding derives from solving a system of differential equations for participants' expected utilities under stochastic conditions, ensuring mathematical rigor. Data from the JD case further corroborates this acceleration effect: post-blockchain implementation, system convergence time decreased from an expected 30-time units to 20-time units, with significantly reduced volatility. These results transcend simplistic incentive-driven transformation arguments, providing policymakers with precise, data-driven guidance for designing incentive structures in volatile agricultural supply chains to accelerate sustainable practice adoption while maintaining system stability.

(3) By systematically exploring parameter variations within the mathematically proven stability region, we identify strategy configurations that achieve cost-effective outcomes by balancing economic and environmental objectives. The analysis demonstrates that trust premiums generated by digital technologies, coupled with moderate regulatory interventions, can reduce overall transition costs by 15–20%. The JD case validates this theoretical prediction: Despite a 200% increase in green production costs, the 300% price premium and 3.5-fold sales growth enabled by blockchain certification yields significantly positive net benefits. The study elucidates how technology-driven market trust offsets the financial burdens of green production, offering supply chain managers a mathematically grounded strategy for implementing sustainable practices without compromising economic viability, and clarifying pathways to align environmental goals with operational realities in agricultural supply chains.

Based on the findings, we propose the following measures to promote the sustainable development of the green agri-food product supply chain.

(1) Reducing the threshold for green transformation through phased cost subsidies: Based on the cost differential threshold identified by the model and validated by the JD case, a "three-year

declining" subsidy strategy is proposed. In the first year, subsidies should cover 40% of the incremental costs of green production to ensure farmers' profits are not lower than those from conventional production. In the second year, subsidies decrease to 30%, leveraging economies of scale and learning curve effects to reduce actual costs. By the third year, subsidies drop to 20%, as the market premium mechanism is largely established. Additionally, a technical assistance fund should be created to provide farmers with zero-interest loans for purchasing monitoring equipment, repayable in installments through future sales revenue.

(2) Establishing a "certification-traceability-premium" market trust system: The JD case demonstrates that a 45% consumer scanning rate directly translates into a 3.5-fold increase in sales. Therefore, a national blockchain traceability platform for agricultural products should be established, initially funded by government investment for infrastructure, with operations later sustained through transaction fees. Products obtaining organic certification must be mandatorily integrated into the traceability system. Concurrently, a "green agricultural product consumption voucher" program should be introduced, offering a 5% cashback reward to consumers who verify products via scanning, fostering green consumption habits. Dedicated "traceable agricultural product zones" should be established in supermarkets in major cities to enhance brand recognition through spatial clustering.

(3) Designing a dynamic regulatory mechanism based on market maturity: A three-stage regulatory strategy is proposed. In the startup phase (adoption rate <30%), stringent regulation should be enforced, including environmental taxes on non-green production and equivalent subsidies for green production. In the growth phase (30%–60%), the focus shifts to incentives, prioritizing support for technological innovation and brand building, with subsidies gradually reduced to 3%. In the maturity phase (>60%), light-touch regulation is implemented, maintaining order through market access standards and information disclosure systems. A quarterly evaluation mechanism should be established to dynamically adjust policy intensity based on actual adoption rates, avoiding excessive intervention or premature withdrawal.

(4) Building an agricultural Data-Sharing platform to reduce market uncertainty: Drawing on JD's experience of reducing return rates through data transparency, a provincial agricultural big data center should be established to integrate multisource data, including weather, prices, inventory, and logistics, made freely accessible to farmers and wholesalers via API interfaces. The platform should include a real-time price alert system, intelligent planting recommendations, and supply-demand matching services.

Building on our theoretical foundation, researchers should focus on empirical validation using multi-regional agricultural data and extension to international supply chain networks. We recommend developing dynamic policy adjustment algorithms based on real-time market feedback and exploring the integration of emerging technologies such as artificial intelligence and satellite monitoring systems. Additionally, longitudinal studies examining the long-term impacts of our proposed policies would provide valuable insights for sustainable agricultural transformation.

While our model focuses on three-agent interactions, future work could incorporate consumer behavior dynamics and international trade considerations. The stochastic framework developed here provides a foundation for exploring more complex market scenarios and policy interactions, opening avenues for comprehensive agricultural ecosystem modeling.

Author contributions

Zheng Wen: Methodology, Software, Writing-original draft, Data curation, Investigation; Ming Mo: Resources, Validation, Writing-review and editing. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

During the preparation of this work the authors used ChatGPT in order to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Conflict of interest

The authors declare there is no conflict of interest.

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