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Collaborative Governance Mechanisms for Farmers' Low-Carbon Transition: A Stochastic Evolutionary Game Perspective

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Abstract

Farmers' low-carbon transition has become a critical issue for achieving sustainable agricultural development. Fundamentally, this transition is driven by multi-actor collaboration and is subject to stochastic disturbances. However, the collaborative governance mechanisms that facilitate farmers' low-carbon transformation remain insufficiently understood, particularly under the influence of random factors. To address this gap, we construct a four-party game model involving farmers, government, enterprises, and financial institutions by employing a stochastic evolutionary game approach that incorporates random disturbance factors to capture real-world uncertainty. Numerical simulations are conducted to examine how different policy tools and external environments shape the system's evolutionary path. The results show the following: (1) In the early transition stage, external uncertainties cause notable fluctuations in strategy evolution, during which the government, farmers, and enterprises gradually form a collaborative mechanism, while financial institutions remain reluctant to participate due to risk and policy uncertainty. (2) Government subsidies, profit returns, and risk-sharing mechanisms exhibit a substitutive relationship, and an appropriate mix of these tools can effectively enhance the willingness of farmers and enterprises to adopt low-carbon practices. (3) Excessive government incentives may crowd out the role of green credit from financial institutions. (4) The profit-sharing ratio among farmers exerts the strongest motivational effect in the early stage, while higher levels of risk-sharing and reputation benefits are more effective in stabilizing the system structure and enhancing transition resilience. This study reveals the dynamic mechanisms of multi-actor interaction in agricultural low-carbon transition and provides theoretical and policy insights for differentiated government strategies and collaborative emission reduction.

Keywords: farmers; financial institutions; low-carbon transition; evolutionary game; stochastic disturbance

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1. Introduction

Under the guidance of the "dual carbon" goals, farmers—being key units of agricultural carbon emissions—are central to achieving sustainable agricultural development [1]. However, limitations in technology capacity, financial investment, and information access still create significant barriers for farmers in adopting low-carbon technologies and shifting to green production methods [2]. At present, the independent capacity for low-carbon innovation in China's agricultural sector remains weak. Rural areas lack efficient mechanisms for the supply of low-carbon technologies. Relying on farmers alone cannot meet the diversified and region-specific demands of low-carbon transition [3]. In this context, multi-actor collaboration has become essential. By integrating resources from policies,

technologies, markets, and information, it is possible to build a cooperative mechanism that shares resources, distributes risks, and aligns interests. Such collaboration is key to overcoming the difficulties of promoting low-carbon practices and implementing technologies on the ground [3,4]. Therefore, exploring how multiple actors can jointly promote farmers' low-carbon transition is of great significance.

Farmers' low-carbon transition requires the cooperation of professionals in agricultural science, environmental engineering, and energy technology. It also depends on the active participation of government agencies, agricultural enterprises, and financial institutions [5]. However, agricultural production is highly diverse, with significant regional differences. Farmers also differ in cognitive capacity, resource endowment, and behavioral preferences. As a result, the low-carbon transition process shows characteristics of multi-objective decision-making, temporariness, and dynamic stage-based evolution [6]. Farmers' behavioral choices are often non-deterministic and adaptive. They are shaped by expected returns, strategies of neighboring farmers, policy intervention intensity, and external support. These choices also change and evolve over time. Consequently, promoting low-carbon transition collaboratively faces many real challenges [4]. For example, differences in transition goals, participation motives, and resource input across actors, combined with poor communication, inadequate incentives, and unclear risk-sharing arrangements, can lead to friction and cooperation failures. In particular, when decisions are influenced by learning effects and environmental changes, transition paths display high dynamic volatility and stochastic strategy evolution, further increasing the complexity of collaboration mechanisms [7].

Financial institutions play a dual role in farmers' low-carbon transition: as system coordinators and as resource enablers. On one hand, tools such as green credit, agricultural carbon insurance, and carbon revenue rights financing can effectively reduce farmers' financial and risk pressures during transition [8]. On the other hand, financial institutions collaborate with governments and enterprises to establish green finance incentives, improving the efficient flow of resources, technologies, and capital within the agricultural low-carbon system [9]. Studies show that combining "formal institutional arrangements" (e.g., carbon asset mortgage loans) with "informal cooperative relationships" (e.g., long-term trust-based credit mechanisms) can stimulate farmers' willingness to transition while ensuring financial security. This also enhances the sustainability of low-carbon practices [10]. Therefore, understanding the participation and guidance mechanisms of financial institutions in collaborative governance is critical for improving the quality of agricultural green transition.

Previous studies have primarily emphasized how governments guide and regulate farmers' behaviors through policy instruments [11]. However, literature that systematically examines farmers' low-carbon transition from a multi-actor collaborative perspective remains limited. The theoretical understanding of the role of financial institutions in collaborative governance—and their influence on the evolution of farmers' low-carbon behaviors—is particularly insufficient, and a comprehensive analytical framework has yet to be established. Therefore, this study aims to address two key questions:

(1) How can farmers' low-carbon transition be guided and incentivized from a multi-actor collaborative perspective?
(2) Under random disturbances, what outcomes emerge within the transition system, and through which policy instruments can stable behavioral evolution be achieved?

This study seeks to answer these questions by revealing how multi-actor collaboration promotes farmers' low-carbon transition and mitigates the influence of randomness on behavioral choices. In other words, it uncovers the transition pathways through which farmers achieve low-carbon transformation under stochastic disturbances. Accordingly,

we construct an evolutionary game model involving farmers, governments, financial institutions, and agricultural enterprises, incorporating both stochastic perturbations and dynamic evolutionary characteristics. The model examines the stability conditions of farmers' low-carbon strategies under random disturbances and, through numerical simulations, explores how variations in collaborative factors shape the behaviors of different stakeholders.

Compared with previous studies, this research offers two main contributions. First, it expands the analytical framework of farmers' low-carbon transition. By adopting a collaborative governance perspective, it addresses the limitations of studies focusing solely on government-driven incentives and highlights the coordinated role of multiple actors. Second, it enriches the theoretical foundation of evolutionary game analysis in farmers' low-carbon transition. By integrating stochastic disturbances—an inherent element of real-world behavior—it more accurately captures the nonlinear characteristics of the transition process and extends the theoretical dimension of the game-theoretic framework.

The structure of this paper is as follows: Section 2 reviews the related literature; Section 3 develops the stochastic evolutionary game model and derives the stability conditions of the trivial equilibrium; Section 4 conducts numerical simulations to analyze stakeholder behavior in farmers' low-carbon transition; and Section 5 discusses the main findings.

2. Literature Review

2.1. Studies on Farmers' Low-Carbon Transition

With the ongoing advancement of the "dual carbon" goals, farmers' low-carbon transition has become a critical topic in agricultural green development. Existing studies have examined this issue from perspectives such as policy incentives [2], farmers' behavioral intentions [12], and technology adoption [13], exploring both internal mechanisms and external drivers. Progress has been made in policy tool design, behavioral economics analysis, and institutional arrangements [14]. However, research that systematically addresses farmers' low-carbon transition from a multi-actor collaborative perspective remains limited. Neglecting this perspective risks underestimating the interaction among stakeholders such as governments, enterprises, and financial institutions. This can result in fragmented policy implementation, insufficient endogenous motivation among farmers, and lower efficiency and sustainability in the transition process.

The concept of low-carbon transition originated from carbon footprint studies proposed by international environmental experts [15] and has since gained increasing attention. Some scholars have extended it to agriculture, focusing on farmers' low-carbon transition. Some scholars have defined farmers' low-carbon transition as a process in which farmers adopt low-carbon technologies and management practices—such as energy conservation, emission reduction, and green circular agriculture—during agricultural production to reduce carbon emissions and enhance ecological outcomes [16]. This process not only supports environmental protection but also strengthens agricultural resilience and farmers' income [16]. Early studies mainly examined farmers' awareness, willingness to adopt low-carbon technologies, and the influence of policy incentives, aiming to explain whether and why farmers are willing to transition [17–21]. As the demand for low-carbon transition has grown, scholars have recognized that it is not solely the result of individual rational choice but also a systemic behavioral evolution driven by multiple external forces. This has led to growing attention to stakeholder collaboration in promoting farmers' low-carbon transition.

For example, Chen et al. analyzed the effects of different subsidy policies on farmers' production decisions and found that government subsidies could increase farmers' green planting area [22]. Aung analyzed the factors influencing farmers' adoption of mobile

agricultural technologies in eastern Thailand and found that targeted government training, subsidies, and improvements in digital infrastructure can promote the large-scale adoption of agricultural technologies [23]. Cammarata collected data from 241 Italian farmers in the Sicily region on their participation in low-carbon sequestration and found that, in addition to the effects of capability and confidence in knowledge, extension services and technical support provided by policymakers and practitioners play a crucial role [24].

Some studies have also begun to consider the role of non-government actors—such as cooperatives and agricultural enterprises—in the transition process. These actors can enhance farmers' green production capacity through agricultural socialized services or promote low-carbon technology adoption via market mechanisms for agricultural products [25,26]. However, most research still focuses on the bilateral relationship between governments and farmers. Few studies capture the dynamic interactions among multiple actors, making it difficult to fully explain the collaborative evolution of low-carbon behavior in complex systems.

In particular, the role of financial institutions as a key supporting actor in farmers' low-carbon transition has received limited attention. Current research on green finance largely concentrates on the macro-level development of carbon finance or the evaluation of agricultural green credit policies. There is a lack of systematic analysis on how financial institutions form collaborative relationships with other actors and how they influence farmers' low-carbon behavior through both formal and informal mechanisms. Therefore, when analyzing the collaborative promotion of farmers' low-carbon transition, the coordinating role of financial institutions should not be overlooked.

2.2. Farmers' Low-Carbon Transition and Game Theory

In recent years, game theory has become an important tool for analyzing complex decision-making behaviors. It has been widely applied to studies of farmers' environmental behavior [27]. Evolutionary game theory, in particular, has emerged as a key method for simulating the behavioral evolution of farmers in the low-carbon transition. Its strength lies in modeling how strategies evolve over time through dynamic interactions within a group. Typical studies adopt classical evolutionary rules such as replicator dynamics. They examine how policy incentives [28], social interactions [29], and risk preferences [30] influence strategy choices. This provides a theoretical foundation for understanding the evolution of farmers' low-carbon behavior. However, our review shows that most existing evolutionary game models rely on deterministic frameworks. They generally assume that farmers update strategies in a stable environment according to payoff differences. Such models ignore the randomness and uncertainty that are common in real-world decision-making. In practice, farmers' choices are influenced by incomplete information, limited cognition, peer imitation, changes in policy expectations, and external disturbances. Ignoring these stochastic factors risks disconnecting models from reality, which may reduce the effectiveness of policy interventions.

Evidence suggests that farmers are not fully rational in their environmental decisions. Their choices are shaped by bounded rationality, peer imitation, experiential learning, and shifting policy expectations [31,32]. Quevedo et al. [19] found that, in rural areas, differences in information access and technical comprehension lead to significant fluctuations in farmers' adoption of low-carbon technologies. Hamidoğlu's study shows that subsidy rates, agricultural product market prices, subsidy amounts, and blockchain markets all influence farmers' decision-making, exhibiting both positive and negative effects [33]. Further showed that farmers' behavior exhibits path dependence, and that policy adjustments or changes in neighbors' behavior can trigger abrupt strategy shifts [34].

Therefore, stochasticity should not be overlooked when studying farmers' low-carbon transition. Introducing randomness into evolutionary game models can improve their explanatory power and capture nonlinear and abrupt changes in system evolution. In this study, Gaussian white noise is used to simulate both internal and external disturbances. We construct an evolutionary game framework with stochastic disturbance terms to describe farmers' behavioral evolution under collaborative interventions. This approach enables the simulation of key factors influencing farmers' low-carbon transition, thereby providing support for more targeted and adaptive low-carbon policies.

3. Stochastic Evolutionary Game Model of Farmers' Low-Carbon Transition

3.1. Research Problem

In the process of farmers' low-carbon transition, four key actors—farmers, government, enterprises, and financial institutions—differ significantly in resources, behavioral preferences, and goal orientations. Together, they form a typical multi-agent, interest-driven, and competitive–cooperative system. The core of the game lies in several issues: whether farmers respond to government incentive policies; whether financial institutions provide green credit support; whether enterprises assume responsibility for collaborating with farmers in the transition; and how the parties address inconsistencies and uncertainties in benefit sharing and cost allocation.

Under bounded rationality, none of the actors can accurately predict future strategies. Their strategic choices rely heavily on local information, peer imitation, and dynamic adjustment. During this process, behaviors are also affected by external uncertainties such as policy fluctuations, information disturbances, and technological risks.

Traditional static game models are insufficient to capture this evolutionary process. In contrast, stochastic evolutionary game theory offers clear advantages. It can describe bounded rationality, the dynamic nature of strategy adjustments, and the role of random disturbances in decision-making. This makes it suitable for simulating multi-agent evolutionary games in complex interactive environments. It also enables the identification of the underlying mechanisms and equilibrium paths of collaborative low-carbon transitions.

3.2. Research Assumptions

Assumption 1. *In the game of farmers' low-carbon transition, the participants include farmers, government, enterprises, and financial institutions. Farmers act as the main implementers of low-carbon technology transformation. The government serves both as a promoter and a regulator of this transformation. Enterprises are willing to cooperate with farmers in low-carbon transition and are important actors in the process. Green credit from financial institutions strengthens the willingness of farmers and enterprises to adopt low-carbon strategies. All four actors are boundedly rational and have no forecasting ability in advance. Their interests differ, yet they remain interdependent in the game process.*

Assumption 2. *Farmers can choose between two strategies: low-carbon transition or non-low-carbon transition. The probability of choosing low-carbon transition is* $x \in [0, 1]$*, and the probability of choosing non-low-carbon transition is* $1 - x$*. Low-carbon transition refers to upgrading production through green technologies. Non-low-carbon transition refers to maintaining traditional production methods. Similarly, the government also has two strategies: active promotion or passive promotion. The probability of active promotion is* $y \in [0, 1]$*, and passive promotion is* $1 - y$*. Active promotion means the government invests manpower, material resources, financial subsidies, and other supports for farmers' low-carbon transformation. Passive promotion means the government issues relevant policies but does not supervise their implementation. Financial institutions can*

choose to provide green credit or not. The probability of providing green credit is $z \in [0, 1]$*, and the probability of not providing it is* $1 - z$*. Green credit refers to loans offered to farmers and enterprises to support low-carbon activities. Non-green credit means no such targeted financial support. Enterprises can choose cooperation or non-cooperation. The probability of cooperation is* $w \in [0, 1]$*, and non-cooperation is* $1 - w$*. Cooperation means that enterprises bear costs to work with farmers in low-carbon transition. Non-cooperation means "free-riding" on the benefits generated by farmers' transition without sharing the cost.*

Assumption 3. *When farmers adopt low-carbon technologies, they obtain a basic return T and bear a cost* π*, including technical and labor costs. When they choose non-low-carbon transition, the basic return is U, and costs are negligible due to reliance on traditional techniques.*

The government gains a social return R from farmers' low-carbon transformation. Under active promotion, the government provides a subsidy δ_1 and a carbon tax rebate δ_2 to farmers. It also provides an incentive Q to enterprises for cooperation and imposes a penalty V on free-riding behavior. Active promotion requires the government to bear a cost μ. If farmers choose non-low-carbon transition under active promotion, the government imposes a constraint cost F on them. If the government adopts passive promotion and farmers choose non-low-carbon transition, the government faces an accountability cost σ imposed by higher authorities.

Assumption 4. *Green credit refers to a category of financial instruments through which financial institutions allocate credit resources with the aim of promoting environmental protection and carbon reduction. Its core features include capital-support functions, risk identification attributes, and policy coordination mechanisms. In the process of farmers' low-carbon transition, financial institutions provide financial support to farmers adopting low-carbon practices through green credit. Given the dual policy-driven and commercial nature of green credit—characterized by capital input, risk exposure, and policy synergy—financial institutions obtain a basic return m when issuing green credit while incurring an operational cost c. Financial support to farmers is denoted as e, and support to enterprises as g, jointly forming the investment structure of green credit.*

When both the government and financial institutions actively promote low-carbon transition, they receive additional reputation gains τ_1 and τ_2, respectively; in contrast, no reputation gain is generated under passive government behavior. Under active government promotion, financial institutions also receive a green credit incentive *M*—which may take the form of subsidies, regulatory facilitation, or operational benefits. If financial institutions still choose non-green credit under this condition, they incur a constraint cost *N*, reflecting regulatory pressures and compliance requirements.

Green credit is exposed to farmers' default risk, with an expected loss of ε. Under active government promotion, this risk is shared between the government and financial institutions, with the latter bearing a proportion θ of the risk; under passive government behavior, financial institutions bear the risk entirely. This mechanism reflects the systemic characteristics of the "return–cost–risk" structure embedded in green credit and highlights the critical role of government policies in lowering the participation threshold for financial institutions and enhancing their willingness to supply green credit.

Assumption 5. *When enterprises cooperate with farmers, the total benefit of their joint low-carbon transition is K. Farmers' share of the cooperative benefit is* $\omega \in [0, 1]$*, and enterprises' share is* $1 - \omega$*. The total cooperation cost is d, with farmers bearing a proportion* φ *and enterprises bearing* $1 - \varphi$*. If either party refuses to cooperate, the non-cooperating side gains a free-riding benefit S, and the cooperating side loses the same amount.*

If none of the four actors promotes low-carbon transition, there is a social loss H caused by non-low-carbon production. While such losses are typically borne by society as

a whole, for modeling purposes, they are allocated among the four actors. The loss-sharing ratios are α for farmers, β for government, γ for financial institutions, and λ for enterprises, with α + β + γ + λ = 1.

The above parameters are summarized in Table 1.

Table 1. Definitions of parameters.

Parameter	Definition	Range
T	Basic benefits of farmers' low carbon transformation	$T > 0$
π	Low carbon transformation cost of farmers	$\pi > 0$
U	Basic benefits of farmers' non low carbon transformation	U > 0
R	Social benefits obtained by the government due to the low carbon transformation of farmers	R > 0
δ_1	Government incentives and subsidies for farmers' low carbon transformation	$\delta_1 > 0$
δ_2	Government carbon tax return for low carbon transformation of farmers	$\delta_2 > 0$
Q	Government incentives and subsidies for low carbon transformation of enterprise cooperation	Q > 0
V	Government punishment for non cooperative "free riding" of enterprises	V > 0
μ	The government actively promotes the cost of low-carbon transformation	$\mu > 0$
F	Government constraints on Farmers' non low carbon transformation	$F > 0$
σ	Accountability costs of higher government departments to government departments	$\sigma > 0$
m	Basic benefits of green credit implemented by financial institutions	$m > 0$
c	Cost of implementing green credit by financial institutions	$c > 0$
e	Financial institutions' financial support to farmers	$e > 0$
g	Financial institutions' financial support to enterprises	g > 0
τ_1	The government actively promotes reputation gains	$\tau_1 > 0$
τ_2	Reputation benefits of financial institutions' implementation of green credit	$\tau_2 > 0$
M	Government incentives for financial institutions to implement green credit	$M > 0$
N	The government's restriction on financial institutions not implementing green credit	N > 0
ε	Expected risk loss	$\varepsilon > 0$
θ	Expected risk loss sharing ratio of financial institutions	$\theta \in [0, 1]$
K	Total benefits of low carbon transformation of farmers and enterprises	K > 0
ω	Proportion of farmers' income distribution	$\omega \in [0, 1]$
d	Cooperation cost of farmers' low carbon transformation	$d > 0$
φ	Cost sharing ratio of farmers	$\varphi \in [0, 1]$
S	"Free rider" benefits of non low carbon transition parties	S
H	Social losses of non joint promotion of low carbon transformation	H
α	Proportion of farmers' share of social losses in non joint promotion of low carbon transformation	$\alpha \in [0, 1]$, and $\alpha + \beta + \gamma + \lambda = 1$
β	Government share proportion of social losses in non joint promotion of low carbon transformation	$\beta \in [0, 1]$, and $\alpha + \beta + \gamma + \lambda = 1$
γ	Financial institutions' share of social losses in non joint promotion of low carbon transformation	$\gamma \in [0, 1]$, and $\alpha + \beta + \gamma + \lambda = 1$
λ	Share of social losses among enterprises not jointly promoting low-carbon transformation	$\lambda \in [0, 1]$, and $\alpha + \beta + \gamma + \lambda = 1$

The payoff matrix for farmers, government, financial institutions, and enterprises is constructed based on the research hypotheses, as shown in Table 2.

Table 2. Payoff matrix for farmers, government, financial institutions, and enterprises.

		Financial Institutions Implement Green Credit (z)		**Financial Institutions Do Not Implement Green Credit ($1-z$)**	
		Enterprise Cooperation (w)	**Enterprises Do Not Cooperate($1-w$)**	**Enterprise Cooperation (w)**	**Enterprises Do Not Cooperate($1-w$)**
Low carbon transformation of farmers (x)	The government actively promotes (y)	$T-\pi+\delta_1+\delta_2+e+\omega\mathrm{K}-\varphi\mathrm{d}$ $R-\mu-\delta_1-\delta_2+\tau_1-M-(1-\theta)\varepsilon-Q$ $m-e+\tau_2+M-\theta\varepsilon-c-g$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}+\mathrm{g}+\mathrm{Q}$	$T-\pi+\delta_1+\delta_2+e+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}$ $R-\mu-\delta_1-\delta_2+\tau_1-M-(1-\theta)\varepsilon+V$ $m-e+\tau_2+M-\theta\varepsilon-c$ $\mathrm{S}-\mathrm{V}$	$T-\pi+\delta_1+\delta_2+\omega\mathrm{K}-\varphi\mathrm{d}$ $R-\mu-\delta_1-\delta_2+\tau_1-Q$ $m-N$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}+\mathrm{Q}$	$T-\pi+\delta_1+\delta_2+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}$ $R-\mu-\delta_1-\delta_2+\tau_1+V$ $m-N$ $\mathrm{S}-\mathrm{V}$
	Government passive promotion ($1-y$)	$T-\pi+e+\omega\mathrm{K}-\varphi\mathrm{d}$ R $m-e+\tau_2-\varepsilon-c-g$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}+\mathrm{g}$	$T-\pi+e+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}$ R $m-e+\tau_2-\varepsilon-c$ S	$T-\pi+\omega\mathrm{K}-\varphi\mathrm{d}$ R m $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}$	$T-\pi+\omega\mathrm{K}-\varphi\mathrm{d}+\mathrm{S}$ R m S
Non low carbon transformation of farmers ($1-x$)	The government actively promotes (y)	$U-F+S$ $-\mu+F-M-Q$ $m+M-c-g$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}+\mathrm{g}+\mathrm{Q}-\mathrm{S}$	$U-F$ $-\mu+F-M+V$ $m+M-c$ $-\mathrm{V}$	$U-F+S$ $-\mu+F-Q$ $m-N$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}+\mathrm{Q}-\mathrm{S}$	$U-F$ $-\mu+F+V$ $m-N$ $-\mathrm{V}$
	Government passive promotion ($1-y$)	$U+S$ $-\sigma$ $m-c-g$ $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}-\mathrm{S}$	U $-\sigma$ $m-c$ 0	$U+S$ $-\sigma$ m $(1-\omega)\mathrm{K}-(1-\varphi)\mathrm{d}-\mathrm{S}$	$U-\alpha H$ $-\sigma-\beta H$ $m-\gamma H$ $-\lambda\mathrm{H}$

3.3. Model Analysis

3.3.1. Copying Dynamic Equations

It can be seen from Table 1 that the expected income E_{A1} of farmers adopting the low-carbon transformation strategy is

$$\begin{aligned} E_{A1} = \; & yzw(T-\pi+\delta_1+\delta_2+e+\omega\mathrm{K}-\varphi\mathrm{d})+yz(1-w)(T-\pi+\delta_1+\delta_2+e+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}) \\ & +y(1-z)w(T-\pi+\delta_1+\delta_2+\omega\mathrm{K}-\varphi\mathrm{d})+y(1-z)(1-w)(T-\pi+\delta_1+\delta_2+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}) \\ & +(1-y)zw(T-\pi+e+\omega\mathrm{K}-\varphi\mathrm{d})+(1-y)z(1-w)(T-\pi+e+\omega\mathrm{K}-\varphi\mathrm{d}-\mathrm{S}) \\ & +(1-y)(1-z)w(T-\pi+\omega\mathrm{K}-\varphi\mathrm{d})+(1-y)(1-z)(1-w)(T-\pi+\omega\mathrm{K}-\varphi\mathrm{d}+\mathrm{S}) \end{aligned} \tag{1}$$

The expected return E_{A2} of farmers' adoption of non-low carbon transformation strategy is

$$\begin{aligned} E_{A2} = \; & yzw(U-F+S)+yz(1-w)(U-F)+y(1-z)w(U-F+S)+y(1-z)(1-w)(U-F) \\ & +(1-y)zw(U+S)+(1-y)z(1-w)(U)+(1-y)(1-z)w(U+S) \\ & +(1-y)(1-z)(1-w)(U-\alpha H) \end{aligned} \tag{2}$$

The average income of farmers adopting the mixed strategy is $\overline{E_A}$ and its expression is

$$\overline{E_A} = xE_{A1}+(1-x)E_{A2} \tag{3}$$

Therefore, the replication dynamic equation of farmers' choice of low-carbon transformation strategy is

$$\begin{aligned} F(x) = \frac{dx}{dt} &= x\left(E_{A1}-\overline{E_A}\right) \\ &= x(1-x)[-\alpha Hyzw+\alpha Hyz+\alpha H(y+z)w+(F+\delta_1+\delta_2-\alpha H)y+(e-\alpha H)z-\alpha Hw+T-\pi-S-U \\ &\quad +\alpha H+\omega K-\varphi d] \end{aligned} \tag{4}$$

Similarly, the replication dynamic equations of the government, financial institutions and enterprises can be calculated as shown in Equations (5)–(7).

$$\begin{aligned} F(y) = \frac{dy}{dt} &= y\left(E_{B1}-\overline{E_B}\right) \\ &= y(y-1)[(\beta H-\sigma)xzw+(-\beta H+\sigma+\varepsilon-\theta\varepsilon)xz+(\sigma-\beta H)zw+(\sigma-\beta H)xw+(F+\delta_1+\delta_2-\tau_1+\beta H)x \\ &\quad +(M-\sigma+\beta H)z+(Q+V-\sigma+\beta H)w+\mu-V-F-\beta H] \end{aligned} \tag{5}$$

$$\begin{gathered} F(z) = \frac{dz}{dt} = z(E_{C1} - \overline{E_C}) \\ = z(z-1)[\gamma Hxyw + (\theta\varepsilon - \varepsilon - \gamma H)xy - \gamma H(x+y)w + (e + \varepsilon + \gamma H - \tau_2)x - (M + N - \gamma H)y + (g + \gamma H)w + c - \gamma H] \end{gathered} \tag{6}$$

$$\begin{gathered} F(w) = \frac{dw}{dt} = w(E_{D1} - \overline{E_D}) \\ = w(1-w)[-(\lambda H + g)xyz + (g + \lambda H)yz + (g + \lambda H)xz + \lambda Hxy - \lambda Hx + (Q + V - \lambda H)y - \lambda Hz + K - S - d + \lambda H - \omega K + \varphi d] \end{gathered} \tag{7}$$

3.3.2. Construction of Stochastic Evolutionary Game Model

Since 1 − x, 1 − y and 1 − z in the dynamic equation of decision-making replication of farmers, governments, financial institutions and enterprises are non negative numbers, which will not affect the convergence state of the system, Equations (4)–(7) can be simultaneous and changed to Equation (8):

$$\begin{cases} F(x) = x[-\alpha Hyzw + \alpha Hyz + \alpha H(y+z)w + (F + \delta_1 + \delta_2 - \alpha H)y \\ \quad + (e - \alpha H)z - \alpha Hw + T - \pi - S - U + \alpha H + \omega K - \varphi d] \\ F(y) = y[-(\beta H - \sigma)xzw - (-\beta H + \sigma + \varepsilon - \theta\varepsilon)xz - (\sigma - \beta H)zw - (\sigma - \beta H)xw \\ -(F + \delta_1 + \delta_2 - \tau_1 + \beta H)x - (M - \sigma + \beta H)z - (Q + V - \sigma + \beta H)w - \mu + V + F + \beta H] \\ F(z) = z[-\gamma Hxyw - (\theta\varepsilon - \varepsilon - \gamma H)xy + \gamma H(x+y)w - (e + \varepsilon + \gamma H - \tau_2)x \\ \quad + (M + N - \gamma H)y - (g + \gamma H)w - c + \gamma H] \\ F(w) = w[-(\lambda H + g)xyz + (g + \lambda H)yz + (g + \lambda H)xz + \lambda Hxy - \lambda Hx \\ \quad + (Q + V - \lambda H)y - \lambda Hz + K - S - d + \lambda H - \omega K + \varphi d] \end{cases} \tag{8}$$

In practice, the behaviors of farmers, government, financial institutions, and enterprises are influenced by external decision-making environments. Such influence can cause behavioral disturbances, leading to random mutations in the game process. These mutations often exhibit strong uncertainty in their periodicity. To more accurately describe the behavioral evolution of these actors during the game, Gaussian white noise is introduced to capture the decision-making under external environmental impacts. The equation incorporating white noise is given in Equation (9):

$$\begin{cases} dx(t) = [-\alpha Hyzw + \alpha Hyz + \alpha H(y+z)w + (F + \delta_1 + \delta_2 - \alpha H)y \\ \quad + (e - \alpha H)z - \alpha Hw + T - \pi - S - U + \alpha H + \omega K - \varphi d]x(t)dt + \delta x(t)d\omega t \\ dy(t) = [-(\beta H - \sigma)xzw - (-\beta H + \sigma + \varepsilon - \theta\varepsilon)xz - (\sigma - \beta H)zw - (\sigma - \beta H)xw \\ -(F + \delta_1 + \delta_2 - \tau_1 + \beta H)x - (M - \sigma + \beta H)z - (Q + V - \sigma + \beta H)w - \mu + V + F + \beta H]y(t)dt + \delta y(t)d\omega t \\ dz(t) = [-\gamma Hxyw - (\theta\varepsilon - \varepsilon - \gamma H)xy + \gamma H(x+y)w - (e + \varepsilon + \gamma H - \tau_2)x \\ \quad + (M + N - \gamma H)y - (g + \gamma H)w - c + \gamma H]z(t)dt + \delta z(t)d\omega t \\ dw(t) = w[-(\lambda H + g)xyz + (g + \lambda H)yz + (g + \lambda H)xz + \lambda Hxy - \lambda Hx \\ \quad + (Q + V - \lambda H)y - \lambda Hz + K - S - d + \lambda H - \omega K + \varphi d]w(t)dt + \delta w(t)d\omega t \end{cases} \tag{9}$$

Here, $\omega(t)$ follows a standard Brownian motion. It represents an irregular stochastic fluctuation that can effectively capture the decision-making behavior of governments, enterprises, and farmers under random disturbances. $d\omega(t)$ is the differential of a standard Brownian motion (formally, white noise). When t > 0 and the step size h > 0, its increment $\Delta\omega(t) = \omega(t+h) - \omega(t)$ follows a normal distribution $N(0, h)$. The parameter δ represents the intensity of the stochastic disturbance.

$dx(t), dy(t), dz(t),\ dw(t)$ are Itô stochastic differential equations. They describe the stochastic evolutionary replicator dynamics for farmers, governments, financial institutions, and enterprises, respectively.

3.3.3. Equilibrium Solution and Stability Analysis of the Stochastic Evolutionary Game Model

For a Itô stochastic differential equation, at the initial moment $t = 0$, $x(t) = 0$, $y(t) = 0$, $z(t) = 0$, $w(t) = 0$, Equation (9) admits a solution. This indicates that, in the absence of disturbance factors at the initial state, the system remains in a constant and stable condition. Therefore, the zero solution is the equilibrium solution of Equation (14).

In reality, the game system is inevitably affected by both internal and external disturbances, which influence its stability. It is thus necessary to account for stochastic factors when analyzing the stability of the game system. The following section conducts a stability analysis of the stochastic evolutionary game model based on the determination theorem for Itô stochastic differential equations.

According to the stability determination theorem for stochastic differential equations [34], if a given stochastic differential equation:

$$dx(t) = f(t, x(t))dt + g(t, x(t))d\omega(t), x(t_0) = x_0 \tag{10}$$

Assume that there exists a function $V(t, x)$ and two positive constants c_1, c_2 such that

$$c_1 \mid x \mid^p \leq V(t, x) \leq c_2 \mid x \mid^p,\ t \geq 0$$

① If there exists $\xi > 0$, such that $LV(t, x) \leq -\xi V(t, x)$, $t \geq 0$, then the zero solution of Equation (15) is p-th moment exponentially stable. Moreover, $E \mid x(t, x_0) \mid^p < \frac{c_2}{c_1} \mid x_0 \mid^p e^{-\xi t}$, $t \geq 0$.

② If there exists $\xi > 0$, such that $LV(t, x) \geq -\xi V(t, x)$, $t \geq 0$, then the zero solution of Equation (15) is p-th moment exponentially stable. Moreover,$E \mid x(t, x_0) \mid^p \geq \frac{c_2}{c_1} \mid x_0 \mid^p e^{-\xi t}$, $t \geq 0$ [34].

According to the above stability criterion, let $V(t, x) = x(t)$, $V(t, y) = y(t)$, $V(t, z) = z(t)$, $x, y, z \in [0, 1]$, $c_1 = c_2 = 1$, $p = 1$, $\xi = 1$, $LV(t, x) = f(t, x)$, $LV(t, y) = f(t, y)$, $LV(t, z) = f(t, z)$, Under these settings, the zero-solution p-th moment exponential stability condition of Equation (9) is satisfied, as expressed in Equation (11).

$$\begin{gathered}
x[-\alpha Hyzw + \alpha Hyz + \alpha Hyw + \alpha Hzw + (F + \delta_1 + \delta_2 - \alpha H)y \\
+(e - \alpha H)z - \alpha Hw + T - \pi - S - U + \alpha H + \omega K - \varphi d] \leq -x \\
y[-(\beta H - \sigma)xzw - (-\beta H + \sigma + \varepsilon - \theta\varepsilon)xz - (\sigma - \beta H)zw - (\sigma - \beta H)xw \\
-(F + \delta_1 + \delta_2 - \tau_1 + \beta H)x - (M - \sigma + \beta H)z - (Q + V - \sigma + \beta H)w - \mu + V + F + \beta H] \leq -y \\
z[-\gamma Hxyw - (\theta\varepsilon - \varepsilon - \gamma H)xy + \gamma H(x + y)w - (e + \varepsilon + \gamma H - \tau_2)x \\
+(M + N - \gamma H)y - (g + \gamma H)w - c + \gamma H] \leq -z \\
w[-(\lambda H + g)xyz + (g + \lambda H)yz + (g + \lambda H)xz + \lambda Hxy - \lambda Hx \\
+(Q + V - \lambda H)y - \lambda Hz + K - S - d + \lambda H - \omega K + \varphi d] \leq -w
\end{gathered} \tag{11}$$

By applying the corresponding reductions to the above expression, the condition satisfying Equation (11) can be obtained as follows:

X_1: When x $\in$ (0, 1], the following condition holds, $y \leq \frac{-1-\alpha Hzw-(e-\alpha H)z+\alpha Hw-T+\pi+S+U-\alpha H-\omega K+\varphi d}{-\alpha Hzw+\alpha Hz+\alpha Hw+(F+\delta_1+\delta_2-\alpha H)}$ and $-\alpha Hzw + \alpha Hz + \alpha Hw + (F + \delta_1 + \delta_2 - \alpha H) > 0$ or $y \geq \frac{-1-\alpha Hzw-(e-\alpha H)z+\alpha Hw-T+\pi+S+U-\alpha H-\omega K+\varphi d}{-\alpha Hzw+\alpha Hz+\alpha Hw+(F+\delta_1+\delta_2-\alpha H)}$ and $-\alpha Hzw + \alpha Hz + \alpha Hw + (F + \delta_1 + \delta_2 - \alpha H) < 0$.

Y_1: When y $\in$ (0, 1], the following condition holds, $z \geq \frac{-1+(\sigma-\beta H)xw+(F+\delta_1+\delta_2-\tau_1+\beta H)x+(Q+V-\sigma+\beta H)w+\mu-V-F-\beta H}{(\beta H-\sigma)xw+(-\beta H+\sigma+\varepsilon-\theta\varepsilon)x+(\sigma-\beta H)w+(M-\sigma+\beta H)}$ and $(\beta H - \sigma)xw + (-\beta H + \sigma + \varepsilon - \theta\varepsilon)x + (\sigma - \beta H)w + (M - \sigma + \beta H) < 0$ or $z \leq \frac{-1+(\sigma-\beta H)xw+(F+\delta_1+\delta_2-\tau_1+\beta H)x+(Q+V-\sigma+\beta H)w+\mu-V-F-\beta H}{(\beta H-\sigma)xzw+(-\beta H+\sigma+\varepsilon-\theta\varepsilon)xz+(\sigma-\beta H)zw+(M-\sigma+\beta H)z}$ and $(\beta H - \sigma)xw + (-\beta H + \sigma + \varepsilon - \theta\varepsilon)x + (\sigma - \beta H)w + (M - \sigma + \beta H) > 0$.

Z_1: When x $\in$ (0, 1], the following condition holds, $w \leq \frac{-1+(\theta\varepsilon-\varepsilon-\gamma H)xy+(e+\varepsilon+\gamma H-\tau_2)x-(M+N-\gamma H)y+c-\gamma H}{-\gamma Hxy+\gamma H(x+y)-(g+\gamma H)}$ and $-\gamma Hxy+\gamma H(x+y)-(g+\gamma H) > 0$ or $w \geq \frac{-1+(\theta\varepsilon-\varepsilon-\gamma H)xy+(e+\varepsilon+\gamma H-\tau_2)x-(M+N-\gamma H)y+c-\gamma H}{-\gamma Hxy+\gamma H(x+y)-(g+\gamma H)}$ and $-\gamma Hxy+\gamma H(x+y)-(g+\gamma H) < 0$.

W_1: When w $\in$ (0, 1], the following condition holds, $x \leq \frac{-1-(g+\lambda H)yz-(Q+V-\lambda H)y+\lambda Hz-K+S+d-\lambda H+\omega K-\varphi d}{-(\lambda H+g)yz+(g+\lambda H)z+\lambda Hy-\lambda H}$ and $-(\lambda H+g)yz+(g+\lambda H)z+\lambda Hy-\lambda H > 0$ or $x \geq \frac{-1-(g+\lambda H)yz-(Q+V-\lambda H)y+\lambda Hz-K+S+d-\lambda H+\omega K-\varphi d}{-(\lambda H+g)yz+(g+\lambda H)z+\lambda Hy-\lambda H}$ and $-(\lambda H+g)yz+(g+\lambda H)z+\lambda Hy-\lambda H < 0$.

If the condition $X_1 \cap Y_1 \cap Z_1 \cap W_1$ is satisfied, the zero solution of the stochastic evolutionary system for the government, enterprises, and farmers is moment-exponentially stable. The subsequent analysis will be conducted based on this stable state.

3.3.4. Taylor Expansion of the Stochastic Evolutionary Equation

Due to the inability to obtain a closed-form analytical solution for the nonlinear Itô stochastic differential equation, the stochastic Taylor expansion and Itô's formula are applied for numerical solutions. The stochastic Taylor expansion is given as follows [35].

$$x(t_{n+1}) = x(t_n) + hf(t_n, x(t_n)) + \Delta\omega_n g(t_n, x(t_n)) \tag{12}$$

Consider Equation (10) $dx(t) = f(t, x(t))dt + g(t, x(t))d\omega(t), x(t_0) = x_0, t\epsilon[t_0, T]$, Using the Euler–Maruyama method, the stochastic numerical approximation is performed over the interval $[t_0, T]$. The interval is divided into N subintervals as $t_0 < t_1 < t_2 < \cdots < t_{N-1} < t_N$, with step size $h = \frac{T-t_0}{N}$. Accordingly, by applying Equation (10) to modify Equation (9), Equations (13)–(16) are obtained.

$$\begin{aligned} x(t_{n+1}) = x(t_n) + \quad & [-\alpha Hyzw + \alpha Hyz + \alpha Hyw + \alpha Hzw + (F + \delta_1 + \delta_2 - \alpha H)y + (e - \alpha H)z - \alpha Hw + T - \pi - S - U \\ & + \alpha H + \omega K - \varphi d]x(t_n)h + \delta x(t_n)\Delta\omega_n \end{aligned} \tag{13}$$

$$\begin{aligned} y(t_{n+1}) = y(t_n) + \quad & [-(\beta H - \sigma)xzw - (-\beta H + \sigma + \varepsilon - \theta\varepsilon)xz - (\sigma - \beta H)zw - (\sigma - \beta H)xw - (F + \delta_1 + \delta_2 - \tau_1 + \beta H)x \\ & -(M - \sigma + \beta H)z - (Q + V - \sigma + \beta H)w - \mu + V + F + \beta H]y(t_n)h + \delta y(t_n)\Delta\omega_n \end{aligned} \tag{14}$$

$$\begin{aligned} z(t_{n+1}) = z(t_n) + \quad & [-\gamma Hxyw - (\theta\varepsilon - \varepsilon - \gamma H)xy + \gamma H(x + y)w - (e + \varepsilon + \gamma H - \tau_2)x + (M + N - \gamma H)y - (g + \gamma H)w - c \\ & + \gamma H]z(t_n)h + \delta z(t_n)\Delta\omega_n \end{aligned} \tag{15}$$

$$\begin{aligned} w(t_{n+1}) = w(t_n) + \quad & [-(\lambda H + g)xyz + (g + \lambda H)yz + (g + \lambda H)xz + \lambda Hxy - \lambda Hx + (Q + V - \lambda H)y - \lambda Hz + K - S - d \\ & + \lambda H - \omega K + \varphi d]w(t_n)h + \delta w(t_n)\Delta\omega_n \end{aligned} \tag{16}$$

Next, numerical simulations will be conducted based on the stochastic Taylor expansion to obtain numerical solutions.

4. Numerical Simulation

The prerequisite for numerical simulation is the assignment of relevant parameters. There are three main approaches to parameter assignment. The first is based on the stability results of stochastic dynamic equations. The second relies on data from statistical yearbooks, statistical agencies, or real-world cases. The third combines partial stability results with partial real-world case data. In evolutionary game models, the first approach is more common. This is because few real cases can provide all the data required by the model. Even when such cases exist, the data are often fragmented. Moreover, even when using the same case, differences in data dimensions may lead to significant variations in parameter values. Whether parameters are assigned based on stability results or real cases, the difference lies only in the initial evolutionary path. The effect of parameter changes on evolutionary outcomes, i.e., the sensitivity analysis results, remains the same. Therefore, in

the following section, the case of low-carbon transition among farmers in Anji County is used for numerical analysis to observe the system's evolutionary trends.

4.1. Quantification of Parameters for the Evolutionary Game Model of Low-Carbon Transformation Among Farmers in Anji County

Based on the case of Anji County's transformation, parameters related to the game among farmers, government, financial institutions, and enterprises were quantified. Parameters that are difficult to quantify are presented based on stability analysis results. The parameter quantification is summarized in Table 3.

Table 3. Parameter quantification.

Parameter	Quantitative Data Sources	Quantized Value
T	According to the project situation of Anji County in 2021, the total output value of bamboo industry will reach 20 billion yuan. In order to avoid differences, the quantitative value is set as 2	2
π	According to the stability results, due to the high cost of low-carbon transformation in the early stage, the quantitative value is set as 6	6
U	According to [36] statistics, the total income of Anji County in 2020 is about 9.728 billion yuan, and the non-public budget accounts for about 30%, so the quantitative value is 3	3
R	According to [36] statistics, the government revenue in 2021 is expected to increase by 0.74 billion yuan over 2020, so the quantitative value is 7	7
δ_1	According to the stability results, the quantitative value is set as 1.2	1.2
δ_2	According to the stability results, the quantitative value is set as 1.8	1.8
Q	According to the stability results, the quantitative value is set as 5.8	5.8
V	According to the stability results, the quantitative value is set as 2.2	2.2
μ	According to [37], Anji county invested nearly 10 billion yuan to carry out low-carbon transformation reform, and set its quantitative value as 1	1
F	According to the stability results, the quantitative value is set as 9.5	9.5
σ	According to the stability results, the quantitative value is set as 2.5	2.5
m	According to the stability results, the quantitative value is set as 2	2
c	According to the bamboo forest carbon sequestration series loans of Anji County Rural Commercial Bank in 2022, the quantitative value is set as 3	3
e	According to the amount of bamboo forest carbon sequestration collection and storage trading platform, 47 "carbon sequestration co enrichment loans" were issued to village collectives, with an amount of 0.19 billion yuan;	1.9
g	According to the amount of bamboo forest carbon sequestration trading platform, a total of 0.12 billion yuan of preferential enterprise loans were issued;	1.2
τ_1	According to the stability results, the quantitative value is set as 8	8
τ_2	According to the stability results, the quantitative value is set as 3	3
M	In 2022, Anji County signed a 11.5 billion yuan carbon sequestration capacity improvement project for the transformation and upgrading of the bamboo industry with financial institutions such as the National Development Bank, and set its quantitative value as 1.5	1.5

Table 3. *Cont.*

Parameter	Quantitative Data Sources	Quantized Value
N	According to the stability results, the quantitative value is set as 6	6
ε	According to the amount of "carbon sink co enrichment loan" and preferential enterprise loan issued by Anji County, and considering the loan interest rate, the quantitative value of risk is set as 7.2	7.2
θ	According to the stability results, the quantitative value is set as 0.5	0.5
K	According to the total income difference before and after the low-carbon transformation of Anji County in 2020 and 2021, the quantitative value is set as 8	8
ω	According to the stability results, the quantitative value is set as 0.5	0.5
d	According to the stability results, the quantitative value is set as 5	5
φ	According to the stability results, the quantitative value is set as 0.5	0.5
S	According to the stability results, the quantitative value is set as 4.3	4.3
H	According to the increased amount of government revenue in Anji County, the quantitative value is set as 6	6
α	Based on the comprehensive consideration of real cases, the value is set as 0.2	0.2
β	Based on the comprehensive consideration of real cases, the value is set as 0.4	0.4
γ	Based on the comprehensive consideration of real cases, the value is set as 0.2	0.2
λ	Based on the comprehensive consideration of real cases, the value is set as 0.2	0.2
δ	Considering the uncertainty of internal and external environment changes and decision preferences, the random disturbance coefficient is set to 0.8	0.8

4.2. Initial Evolution Path of Anji County Farmers' Low Carbon Transformation Project System

To avoid the influence of initial decision probabilities of farmers, government, financial institutions, and enterprises on the evolutionary results, the initial probability for all four actors is set to 0.5. Numerical simulation of the initial evolutionary path for the low-carbon transition project in Anji County is conducted using MATLAB 2024b, as shown in Figure 1. From Figure 1, it can be observed that under stochastic disturbance, the strategies of financial institutions converge toward 0 with fluctuations. In contrast, farmers, government, and enterprises converge toward 1 with fluctuations. This indicates that the decision of financial institutions satisfies the matrix zero-solution exponential stability criterion, whereas the other three do not. In fact, the convergence pattern in Figure 1 is strongly correlated with the stochastic disturbance coefficient.

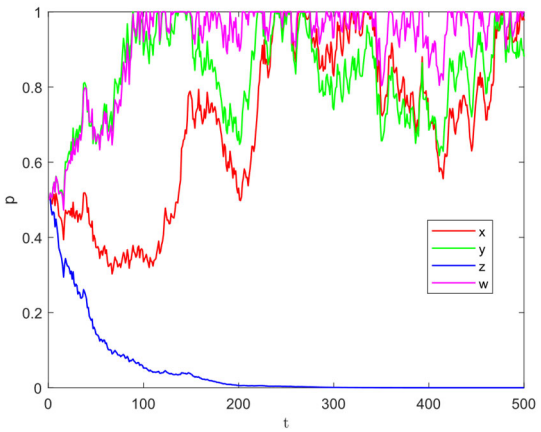


Figure 1. Initial evolution path of Anji County low-carbon transition project system.

When the disturbance coefficient is small or approaches zero, the peak of fluctuations for the three actors decreases, and the curves gradually become smoother. This suggests that under the influence of internal and external environments, the decisions of farmers, government, financial institutions, and enterprises exhibit significant uncertainty. Compared with the classical evolutionary game, the stochastic evolutionary game addresses the limitation of ignoring random disturbances from internal and external factors, thus aligning more closely with real-world conditions. The observed evolutionary outcome is mainly due to the fact that the low-carbon transition in Anji County is still in its early stage. The government is actively promoting the transition, and farmers and enterprises are engaging in deeper cooperation with the government. As a result, the three actors evolve toward full participation (probability 1). However, due to the instability of the early stage and uncertainty in internal and external environments, financial institutions are reluctant to provide substantial green credit. Case data also show that the "carbon sink co-prosperity loan" for village collectives amounts to less than 0.2 billion yuan. Therefore, financial institutions ultimately tend to choose not to implement green credit, in order to avoid their own risks.

4.3. Sensitivity Analysis of Key Decision Parameters in Low-Carbon Transition of Farmers in Anji County

Section 4.1 quantifies the parameters influencing the low-carbon transition of farmers in Anji County. Here, we simulate the impact of parameter variation on system evolution.

(1) Random disturbance coefficient. The coefficients were set as $\delta = 0.2$, 0.5, and 0.8. The corresponding evolutionary results are shown in Figure 2. In the classical evolutionary game, the behavioral decisions of farmers, government, financial institutions, and enterprises are determined by expected payoffs. However, in reality, the low-carbon transition is also affected by changes in internal and external environments. Such uncertainty causes the strategy evolution paths of all stakeholders to deviate from the equilibrium state observed in deterministic games. From Figure 2, the amplitude of the red curve is significantly smaller than that of the green and blue curves. This indicates that the smaller the random disturbance, the weaker the impact of uncertainty on the system. If $\delta = 0$, the decision-making paths of farmers, government, financial institutions, and enterprises would form smooth curves. When the disturbance intensity is 0.5 or 0.8, all four stakeholders exhibit strong fluctuations within certain intervals. For example, farmers fluctuate notably in the 200, 400] interval, while the government does so in the [100, 300] interval. This suggests that the uncertainty of the external environment in Anji's low-carbon transition influences strategy evolution. It further reflects that factors such as information asymmetry and bounded rationality can disturb strategic choices during the transition process. Figure 3 also shows that the stabilization rate of farmers and enterprises is faster than that of the government. This is due to the lag in governmental decision-making when promoting low-carbon transition. As an official institution, the government faces higher promotion and subsidy costs, as well as numerous uncertainties, leading to slower convergence compared to farmers and enterprises. In addition, with greater disturbance intensity, the time required for all stakeholders to reach stability varies. This implies that random disturbance intensity affects not only short-term behavioral decision probabilities, but also the time needed for the system to stabilize. Therefore, under the combined influence of costs, benefits, and random disturbances, the strategic choices of farmers, government, financial institutions, and enterprises are not always optimal. The resilience intensity of the low-carbon transition changes significantly under random factors. The stochastic evolutionary game model, embedded with Gaussian white noise, compensates to some extent for the limitations of the classical deterministic model, which considers only payoffs and produces overly smooth decision-evolution curves.

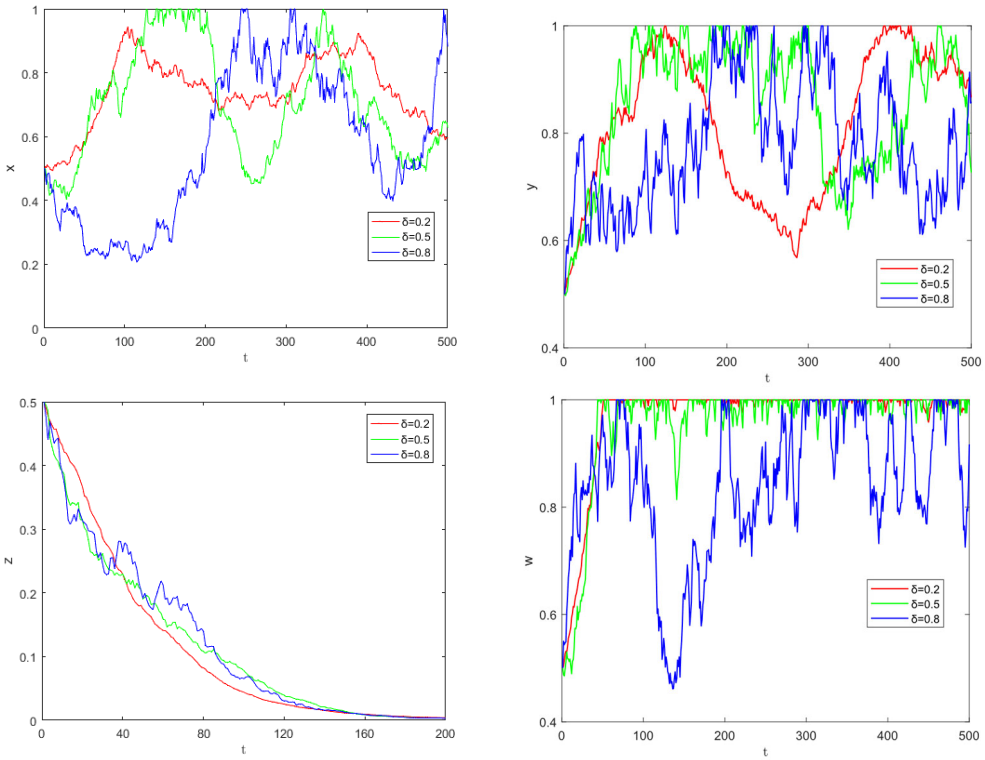


Figure 2. Effect of δ variation on evolution results.

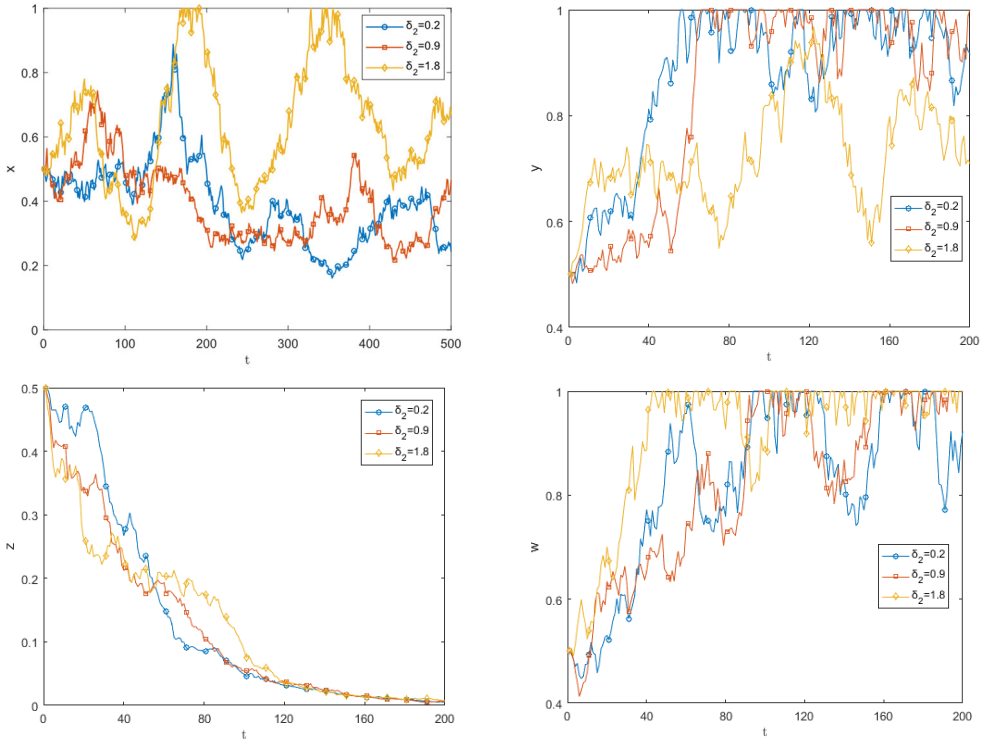


Figure 3. Effect of δ_2 Variation on evolution results.

(2) Carbon tax rebate for farmers' low-carbon technology transition in Anji County. The coefficients were set as δ_2 = 0.2, 0.9, and 1.8. The evolutionary results are shown in Figure 3. As illustrated in Figure 3, a higher carbon tax rebate from the government accelerates farmers' convergence towards low-carbon technology transition. However, the rebate constitutes a cost for the government. Consequently, the government converges slightly faster toward a passive promotion strategy. The increased willingness of farmers

to adopt low-carbon technologies attracts more enterprises to inject capital into Anji's low-carbon transition. As a result, enterprises also converge to a cooperative strategy at a faster rate. Similarly, once farmers receive financial support through the carbon tax rebate, the convergence rate of financial institutions toward providing green credit declines. This decline occurs for two reasons. First, the rebate incentivizes farmers directly, reducing the need for green credit as an additional stimulus. Second, the risk associated with issuing green credit remains relatively high under such conditions. The results indicate that, under the influence of random factors, system evolution still exhibits uncertainty. Overall, however, the carbon tax rebate for farmers—effectively a tax incentive from the government—serves as a partial substitute for green credit from financial institutions.

(3) Social welfare loss when all four parties do not promote low-carbon technology transition. The parameter values were set as H = 3, 6, and 7. The evolutionary results are presented in Figure 4. As shown in Figure 4, an increase in social welfare loss simultaneously encourages farmers to adopt low-carbon technologies, motivates the government to actively promote the transition, drives financial institutions to provide green credit, and induces enterprises to choose cooperation. The incentive effect is more pronounced for farmers than for the other stakeholders. This is because farmers are the ultimate beneficiaries of the low-carbon transition. However, from a long-term perspective, the social welfare loss will continue to increase, with the government typically bearing a larger share of this burden. As a result, the convergence rate of the government toward active promotion shows a gradual slowdown in the later stages.

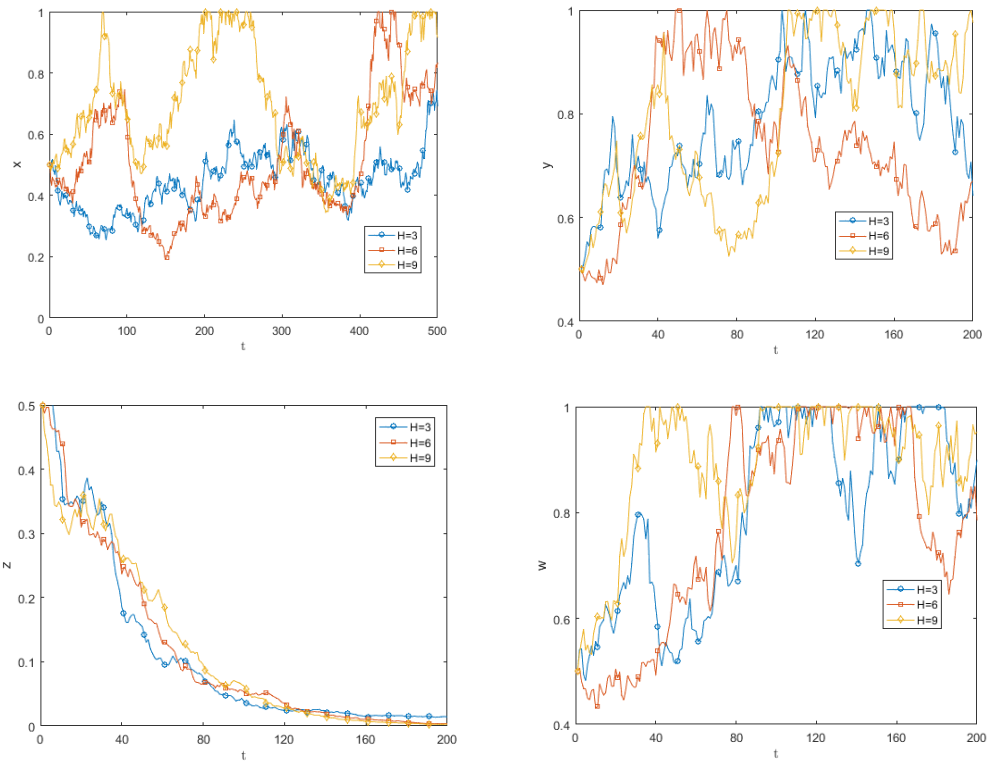


Figure 4. Impact of H change on evolution results.

(4) Government reputation gains when all four parties jointly promote the low-carbon technology transition. The parameter values were set as τ_1 = 2, 4, and 8. The evolutionary results are presented in Figure 5. As shown in Figure 5, an increase in government reputation gains is positively correlated with the joint promotion of low-carbon technology transition by farmers, the government, financial institutions, and enterprises. A higher government reputation gain leads to stronger support for farmers, financial institutions,

and enterprises. Consequently, the convergence rate of farmers toward low-carbon transition is significantly accelerated in the early stage. However, when considering random external disturbances, the overall convergence process exhibits increased volatility. At the same time, the convergence rate of financial institutions toward non-green credit declines noticeably. These results indicate that government reputation gain is a critical parameter influencing system decisions. It can simultaneously incentivize all four stakeholders to advance the low-carbon technology transition.

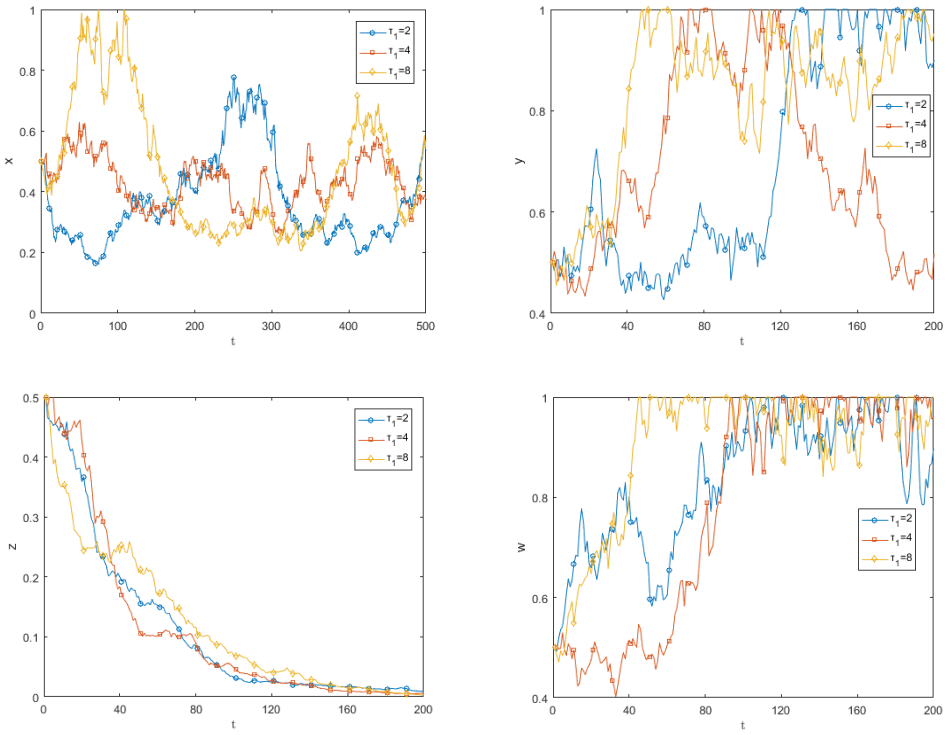


Figure 5. Effect of τ_1 Variation on evolution results.

(5) Green credit incentive subsidies for financial institutions in Anji County. The parameter values were set as M = 1.5, 3, and 6. The evolutionary results are shown in Figure 6. As illustrated in Figure 6, higher green credit incentive subsidies significantly reduce the convergence rate of financial institutions toward non-green credit. However, as subsidies continue to increase, financial institutions realize that implementing green credit is not their dominant strategy. This is because the associated risks become substantial. Consequently, with further increases in subsidies, the rate at which financial institutions choose green credit begins to slow over time. Nevertheless, since the low-carbon transition can bring a substantial increase in the county's GDP, the convergence of financial institutions toward green credit eventually accelerates. The behavioral patterns of farmers show that initial subsidies can also promote their adoption of low-carbon transition. This is consistent with the incentive effect on financial institutions. However, when the incentive level becomes too high, the higher risk borne by financial institutions reduces their willingness to provide green credit to farmers. As a result, the farmers' convergence rate toward low-carbon transition also slows to some extent.

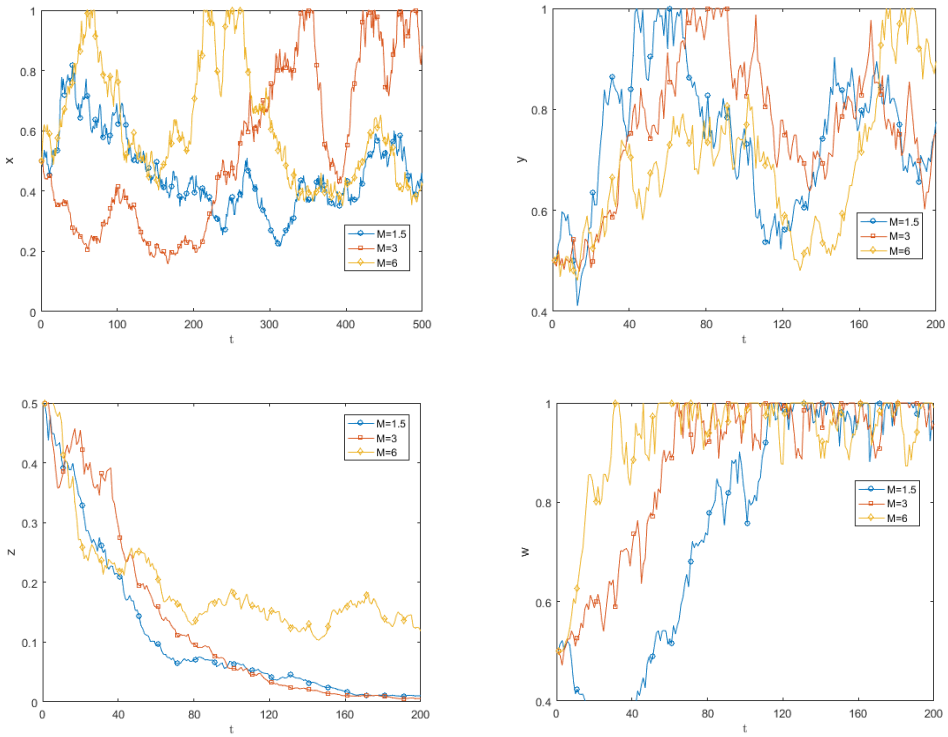


Figure 6. Impact of M change on evolution results.

(6) Financial support for farmers' low-carbon transition. The parameter values were set as e = 6.5, 10, and 15. The evolutionary results are shown in Figure 7. Higher government financial support for farmers' low-carbon technology transition accelerates the farmers' convergence toward low-carbon adoption. However, over time, excessive subsidies increase the financial risk borne by institutions in Anji County. As a result, the convergence rate of financial institutions toward non-green credit accelerates. It is also observed that the government's convergence toward active promotion slows during the early stage. This indicates that financial institutions' support partially substitutes for the government's promotional role. The increased willingness of farmers to adopt low-carbon technologies further promotes the willingness of enterprises to cooperate. Therefore, financial support from financial institutions is a key factor influencing the cooperative low-carbon technology transition between farmers and enterprises in Anji County.

(7) Risk-sharing ratio of financial institutions. The parameter θ was varied within the interval [0, 1]. The evolutionary results are presented in Figure 8. The following four colormaps (cool, autumn, parula, hsv) represent the gradient processes of x, y, z, and w, respectively. As the proportion of risk borne by financial institutions for unpaid green loans increases, their convergence rate toward green credit accelerates. This is due to the higher losses incurred after implementing green credit. When t = 100 and θ = 0, farmers in Anji County converge toward low-carbon technology adoption at a rate close to 1. In contrast, when t = 100 and θ = 1, the convergence rate is around 0.5. This indicates that non-implementation of green credit by financial institutions exerts a positive inhibitory effect on farmers' low-carbon willingness. With the government's share of risk decreasing, its convergence toward active promotion shows an increasing fluctuation trend. As farmers' willingness to adopt low-carbon technologies declines, the convergence rate of enterprises toward cooperation also slows significantly.

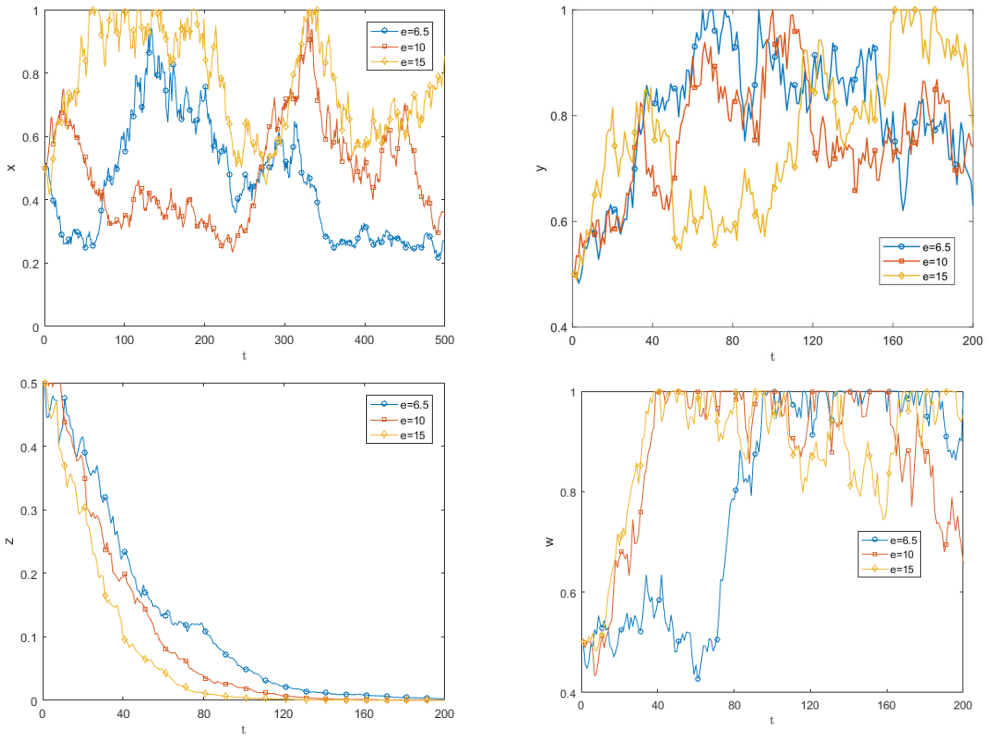


Figure 7. Effect of e change on evolution results.

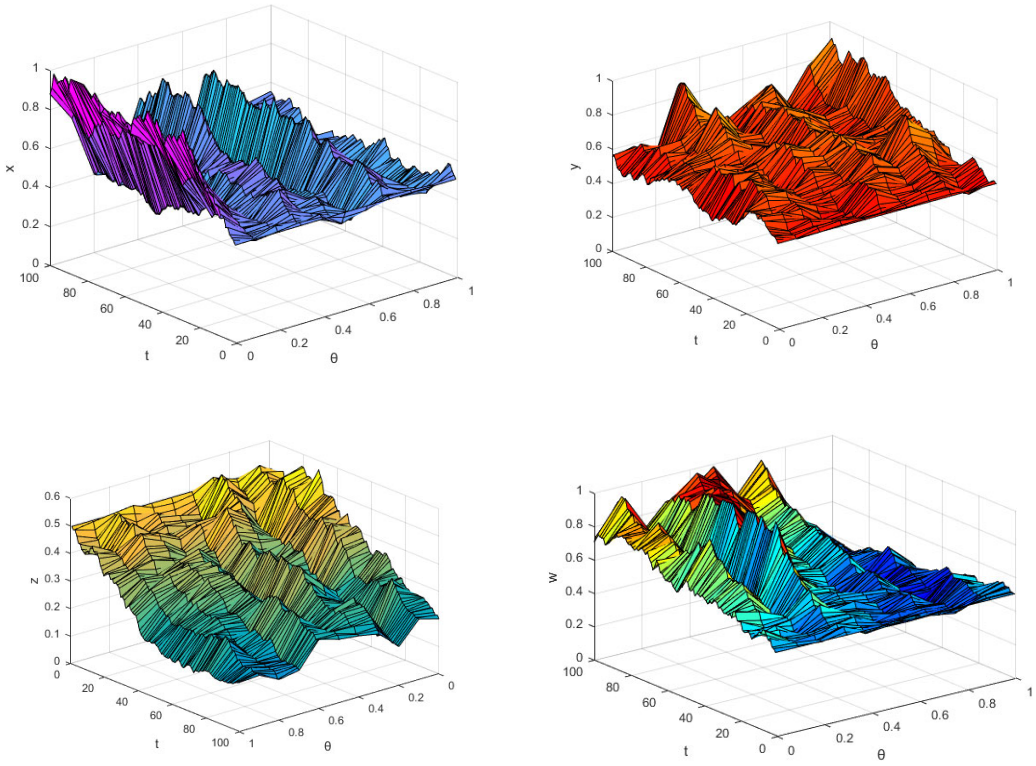


Figure 8. Influence of θ variation on evolution results.

(8) Profit-sharing ratio of farmers in cooperation. The parameter ω was varied within the interval [0, 1]. The evolutionary results are shown in Figure 9. The following four colormaps (summer, hot, jet, spring) represent the gradient processes of x, y, z, and w, respectively. A higher profit-sharing ratio for farmers leads to a faster convergence toward low-carbon technology adoption. When t = 100 and ω = 0, the convergence rate is about 0.1. When t = 100 and ω = 0.8, the rate increases to approximately 0.8. This demonstrates

that the profit-sharing ratio exerts a positive incentive effect on farmers' adoption of low-carbon technologies. Similarly, when farmers' profit share increases, the profit share for enterprises decreases. As a result, the convergence rate of enterprises toward cooperation slows down. The results also indicate that the profit-sharing ratio has a relatively weak sensitivity effect on government behavior. At the same time, the convergence rate of financial institutions toward green credit declines. Without cooperation between enterprises and farmers, farmers' debt repayment capacity tends to decrease. To avoid potential risk, financial institutions reduce their convergence rate toward green credit.

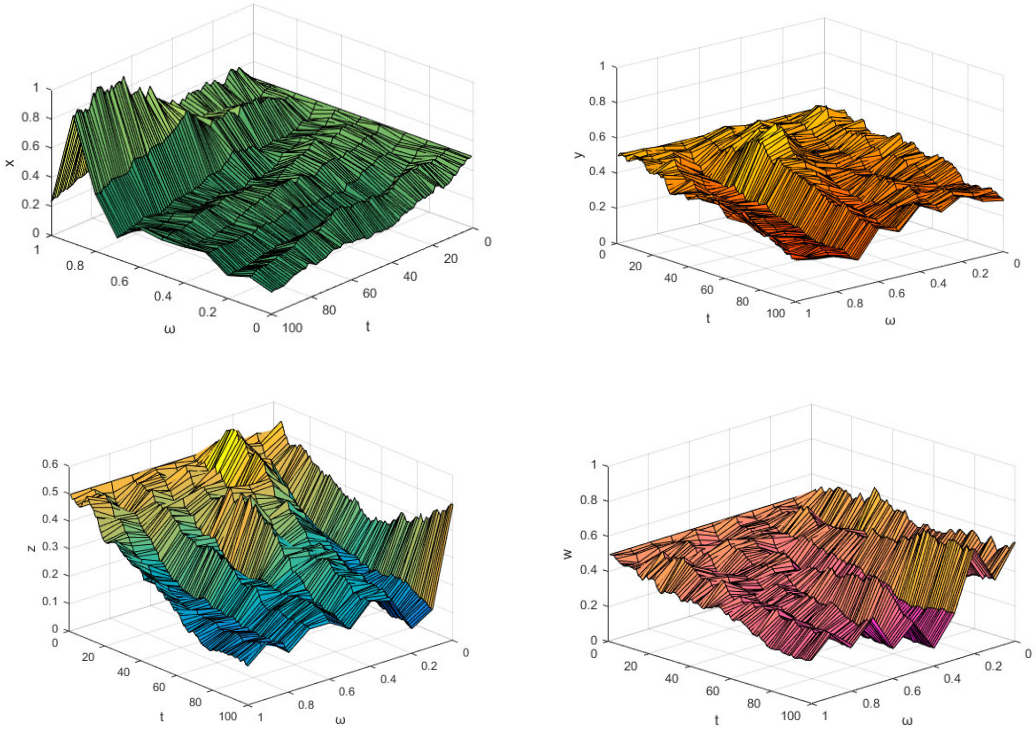


Figure 9. Influence of ω change on evolution results.

(9) Financial institutions' funding support for enterprises. The parameter g was varied within the interval [0, 1]. The evolutionary results are presented in Figure 10. Funding support from financial institutions exerts a positive incentive effect on enterprises' cooperation in low-carbon technology adoption. It also positively stimulates farmers' adoption of low-carbon technologies. This is because such funding increases the expected returns for both enterprises and farmers in Anji County. However, providing funding requires financial institutions to bear higher risks. As a result, their convergence rate toward green credit decreases. With an increase in g, the government's initial convergence rate toward active promotion rises. When g continues to increase, the convergence rate toward 1 slows down. This slowdown is due to the partial substitution effect of financial institutions' funding support for government subsidies, which weakens the government's promotion rate in the later stage.

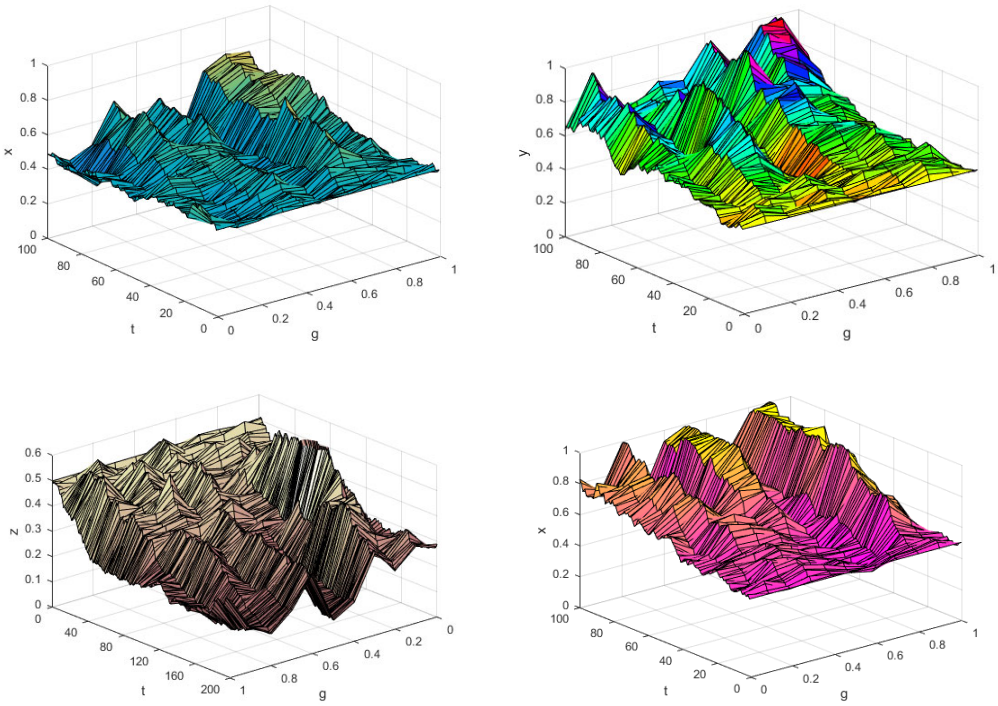


Figure 10. Impact of g change on evolution results.

5. Discussion

5.1. Main Findings

This study focuses on the collaborative promotion of farmers' low-carbon transition. A stochastic evolutionary game model was constructed involving four key stakeholders: farmers, government, enterprises, and financial institutions. The model systematically depicts the strategy evolution of multiple actors under bounded rationality and dynamic interactions. The analysis emphasizes the impact mechanisms of different collaboration patterns on farmers' choices toward low-carbon adoption. The results reveal the critical role of collaborative factors in enhancing farmers' willingness to transition, optimizing resource allocation, and stabilizing system equilibrium. These findings provide theoretical support and decision-making references for building a governance system that integrates multi-actor participation and mechanism linkage to promote green and low-carbon agricultural transformation.

This study first simulated the initial evolutionary paths of farmers, government, enterprises, and financial institutions in Anji County. Compared with the results of previous deterministic evolutionary models [4,6], this study incorporates the stochastic nature of farmers' low-carbon transition. This allows a more realistic representation of the dynamic evolution of policy implementation, financial support, and cooperative behavior in real-world settings. It also provides theoretical support for collaborative governance in low-carbon transition practice. The results show that in the early stage of farmers' low-carbon transition, external uncertainties and behavioral disturbances lead to significant fluctuations and heterogeneity in strategy evolution among multiple actors. Through game interactions, the government, farmers, and enterprises gradually establish a collaborative mechanism and eventually converge on stable strategies that support low-carbon transition. Financial institutions, however, tend to adopt conservative strategies due to credit risk and policy uncertainty, resulting in low willingness to participate. The simulation results are largely consistent with the actual situation in Anji County. At the government level, Anji has in recent years implemented an "eco-points system" to incentivize green production among farmers and promoted collective carbon sink projects, which have effec-

tively increased the willingness of farmers and enterprises to cooperate [38]. For example, the "Yucun Carbon Credit" mechanism enables the sharing of carbon revenue between village collectives and enterprises, encouraging farmers to engage in low-carbon ecological restoration and reflecting the collaborative evolution trend among government, farmers, and enterprises [39]. In contrast, the participation of financial institutions remains limited. The "Carbon Sink Prosperity Loan" program in Anji currently involves relatively small amounts [40] and is mainly targeted at village collectives, with little credit support for individual farmers. This aligns with the model's conclusion that financial institutions tend toward conservative strategies under risk and uncertainty. It also indicates that in the early stage of farmers' low-carbon transition, insufficient financial engagement is a major obstacle to forming an effective collaborative mechanism. Therefore, there is an urgent need to improve green finance incentives and risk mitigation measures to enhance the participation of financial institutions.

Secondly, this study conducted numerical simulations to examine the impact of key parameter variations on evolutionary outcomes. Compared with previous studies that focused on government policy regulation of farmers' low-carbon transition, our results reveal interaction and substitution effects between internal game factors and government policies. The findings show that fiscal subsidies, revenue returns, and risk-sharing mechanisms interact and partially substitute for each other in influencing low-carbon behavioral incentives. Government carbon tax rebates, financial support, and reputation gains can effectively enhance the willingness of farmers and enterprises to adopt low-carbon technologies. However, these measures also exert a "crowding-out effect" on the green credit behavior of financial institutions. The proportion of risk shared between the government and financial institutions determines their relative influence in the system. Overall, the marginal effects of different incentive policies show a declining trend. Institutional design should focus on synergizing multiple incentives and balancing costs to avoid the imbalance caused by reliance on a single policy tool. Huang et al. [21] noted that excessive fiscal subsidies in China's green finance policy could lead financial institutions to reduce green loan issuance, demonstrating a substitution effect. Direct fiscal subsidies may weaken bank incentives and influence their risk assessment and lending intentions. Moreover, a well-designed risk-sharing mechanism between government and financial institutions can stimulate market vitality and promote effective green credit supply [9]. Coordinated and dynamically adjusted multi-incentive policies are essential to achieving a sustainable low-carbon transition for farmers.

Finally, this study analyzed the vertical comparison of parameter variations through numerical simulations, aiming to provide effective pathways for farmers' low-carbon transition. The results indicate that, in the early stage, the proportion of cooperative income allocated to farmers exerts the strongest incentive effect on transition behavior, with a clear decline in marginal effects. Carbon tax rebates and financial support show significant effects at moderate levels, but excessive levels generate substitution effects on financial institutions, weakening system coordination. In contrast, higher levels of risk-sharing and reputation gains are more effective in stabilizing the system structure and enhancing transition resilience. These findings are closely related to the economic structure of Anji County, which is dominated by the bamboo industry and relies on cooperative income for farmers. In this context, early-stage income distribution directly affects farmers' actual earnings, thereby producing the strongest incentive effect [40]. While government subsidies and carbon tax rebates are effective, excessive intervention can suppress the market participation of financial institutions, undermining overall synergy [41]. Risk-sharing and reputation mechanisms are more applicable in the later stages of stable development, aligning with Anji's transition process from incentive-driven change to institution-based security [42,43].

5.2. Theoretical Implications

This study makes two marginal contributions:

First, it develops a four-party evolutionary game model involving farmers, government, enterprises, and financial institutions. From the perspective of collaborative governance, it systematically examines the interaction mechanisms and behavioral evolution paths among multiple actors in promoting farmers' low-carbon transition. This approach addresses the limitations of previous studies that focused mainly on government-led coordination of farmers' low-carbon technology adoption, and it expands the theoretical scope of research on farmers' low-carbon transition.

Second, the model incorporates stochastic disturbance factors to simulate real-world uncertainty, such as information asymmetry and behavioral deviations. A stochastic evolutionary game framework with embedded Gaussian white noise is constructed, which better reflects the volatility and nonlinear evolution observed in actual transition processes. This addition enriches the theoretical dimension of stochastic models and enhances both the explanatory power and practical applicability of the framework.

5.3. Managerial Implications

First, based on the comparison between simulation results and the case of Anji County, policy improvements should focus on multi-actor collaboration and financial incentives. On the financial side, a risk mitigation mechanism should be established to encourage financial institutions to participate in the low-carbon transition. Examples include government-led green guarantee funds and the expansion of carbon sink revenue–pledged loans. These measures can reduce the perceived risks of providing green credit to individual farmers, thereby increasing both the accessibility and willingness of financial institutions to provide support. On the collaboration side, the incentive mechanisms among farmers, enterprises, and the government should be further improved. Carbon ticket systems or carbon revenue-sharing schemes could be promoted to encourage stable partnerships between enterprises and farmers. Such arrangements can strengthen farmers' expectations of low-carbon returns, stabilize their behavior, and foster a sustainable low-carbon transition based on shared responsibility and mutual benefit.

Second, the findings highlight the need to build a coordinated multi-incentive mechanism to avoid the "crowding-out effect" of single policy tools. Government incentives, such as fiscal subsidies and carbon tax rebates, should be moderate in scale to prevent excessive substitution for green credit from financial institutions, which could weaken their lending incentives and risk assessment capacity. The risk-sharing mechanism between the government and financial institutions should be strengthened. This could involve introducing risk mitigation tools, green loan interest subsidies, or loss compensation schemes to stimulate proactive green lending by financial institutions. Moreover, policies should adopt a dynamic adjustment mechanism that allocates fiscal support and financial instruments flexibly in response to market feedback. This would promote a low-carbon transition policy framework in which government guidance, market leadership, and stakeholder collaboration are effectively integrated.

Finally, given that improving the farmers' share of cooperative benefits has the strongest initial incentive effect—though with clear diminishing returns—policy should focus on optimizing benefit distribution mechanisms. This will ensure that farmers receive reasonable and stable economic returns during the early stage of the low-carbon transition, thereby enhancing their motivation and participation. Government fiscal subsidies and carbon tax rebates should remain at appropriate levels to avoid undermining the willingness of financial institutions to provide green credit, which could weaken overall collaboration. Strengthening the risk-sharing mechanism between government and financial

institutions, along with improving reputation-based incentives, will help build a resilient green finance system. Such measures can support a smooth transition from incentive-driven change to institution-based stability, forming a sustainable development pattern driven by government guidance, market participation, and multi-actor collaboration.

6. Conclusions

This study investigates the collaborative mechanisms that drive farmers' low-carbon transition under the influence of stochastic disturbances. To achieve this goal, we constructed a four-party stochastic evolutionary game model involving farmers, government, enterprises, and financial institutions, integrating random disturbance factors to more accurately reflect real-world uncertainty in behavioral decision-making. Through numerical simulations, the model examined how different policy tools, incentive structures, and external conditions shape the dynamic evolution of stakeholder strategies. This framework enables a systematic analysis of both the cooperative behaviors among multiple actors and the stabilizing mechanisms of low-carbon transition under uncertain environments.

The main conclusions are as follows.

(1) External uncertainties significantly affect the early-stage evolution of strategies. Random disturbances lead to pronounced fluctuations and heterogeneity in behavior, during which farmers, government, and enterprises gradually establish a collaborative mechanism that eventually converges toward stable low-carbon strategies. In contrast, financial institutions exhibit persistent reluctance to participate due to credit risks and policy uncertainty.

(2) Government subsidies, profit returns, and risk-sharing mechanisms demonstrate substitutive effects. A balanced combination of these incentives can effectively enhance the willingness of farmers and enterprises to adopt low-carbon practices, whereas relying heavily on a single policy tool reduces overall system efficiency.

(3) Excessive government incentives may crowd out green credit from financial institutions. Over-subsidization weakens the participation motivation of financial institutions, which may undermine long-term collaborative governance in the low-carbon transition.

(4) The relative effectiveness of collaborative factors varies across transition stages. Profit-sharing exerts the strongest motivational effect in the initial stage, directly stimulating farmers' willingness to transition. In later stages, higher levels of risk-sharing and reputation benefits help stabilize system structure and enhance transition resilience.

Overall, this study enriches the theoretical understanding of farmers' low-carbon transition by integrating multi-actor collaboration with stochastic evolutionary dynamics. The findings provide policy insights for designing differentiated and stage-specific incentive mechanisms, strengthening financial participation, and fostering a collaborative governance system that supports resilient and sustainable agricultural low-carbon development.

Although this study offers new perspectives and makes certain theoretical contributions to the low-carbon transition of farmers, it also has some limitations. The research is based on the case of Anji County, which has distinct regional characteristics. The model parameters and results may therefore have limited applicability to other regions. Further investigation is needed to assess their relevance in different contexts. In addition, the behavior of financial institutions in the model is mainly described through the risk-sharing ratio and the level of subsidies. It does not fully account for the influence of financial product innovation, diversified credit mechanisms, or the dynamic changes in financial markets on the transition process. Future research could explore these aspects in greater depth.

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Resources; Software; Supervision; Validation; Visualization; Writing—review & editing. All authors have read and agreed to the published version of the manuscript.

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