

Article

A System Evolutionary Game Analysis of Tripartite Collaborative Disaster Governance Under Dynamic Reward–Punishment in the Guangdong–Hong Kong–Macao Greater Bay Area

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- **Systems practice:** This study conceptualizes cross-jurisdictional disaster governance as an adaptive multi-actor system involving regional coordinating authorities, local emergency management actors, and social participation actors, providing an operational framework for improving collaboration across administrative and institutional boundaries.
- **Systems theory and methodology:** The study extends tripartite evolutionary game analysis by incorporating static, linear dynamic, and nonlinear dynamic reward–punishment feedback mechanisms, enabling systematic comparison of their effects on behavioral evolution, system stability, and collaborative convergence.

What are the main findings and/or the implications of the main findings?

- The findings indicate that the absence of incentives sustains weak collaboration, static mechanisms may increase fiscal burdens and subsidy dependence, and linear dynamic mechanisms may generate strategic oscillations when their feedback structure does not adequately reflect actor heterogeneity and collaborative performance.
- Under the tested assumptions and parameter settings, an optimized nonlinear mechanism combining incremental rewards with progressive constraints promotes convergence toward active leadership, proactive collaboration, and active participation. This supports the use of differentiated subsidies, performance-based rewards, and liability-recovery mechanisms in cross-regional disaster governance.

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Abstract

Disaster governance in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) spans multiple administrative regions, institutions, and platforms, and hazards such as typhoons, storm surges, and urban waterlogging generate strong cross-boundary spillovers that no single city can manage alone. To explain the persistent problems of stakeholder hesitation, underinvestment, and free-riding, this study treats collaborative disaster governance as a multi-actor system and develops a tripartite evolutionary game model linking the regional coordinating regulatory authorities, local emergency management

actors, and social participation actors. Static, linear dynamic, and nonlinear dynamic reward–punishment regimes are embedded into the payoff matrix and examined through stability analysis and numerical simulation. The results show that, without incentives, the system settles into an imbalanced “regulatory authorities-driven, weak collaboration” equilibrium; static mechanisms improve targeted behavior but erode the regulatory authorities’ willingness to lead; and linear dynamic mechanisms induce strategy oscillations in cross-regional settings. Under a parameter-adjusted nonlinear dynamic mechanism that combines incremental incentives with progressive constraints, the tested system converges toward “active leadership–proactive collaboration–active participation” under the assumed cost, benefit, and initial-condition settings. These findings provide a basis for designing differentiated subsidies, performance-based rewards, and liability recovery in GBA disaster governance.

Keywords: collaborative disaster governance; tripartite evolutionary game; dynamic reward–punishment mechanism; system convergence; Guangdong–Hong Kong–Macao Greater Bay Area

1. Introduction

The Guangdong–Hong Kong–Macao Greater Bay Area is a highly open urban agglomeration in China with a dense population and industry and a highly interconnected infrastructure network; it is also an area where multiple risks overlap, including typhoons, heavy rain, storm surges, urban waterlogging, geological hazards, and public safety incidents. Compared with typical urban clusters, the particularity of disaster governance in the Greater Bay Area lies not only in compound hazards and risk spillovers, but also in differences in legal systems, administrative procedures, data rules, rescue standards, and social mobilization methods among the three places under the “one country, two systems” framework. In practice, Guangdong, Hong Kong, and Macau have formed a certain foundation for emergency cooperation, but in specific disaster contexts problems may still arise such as insufficient disaster information sharing, untimely allocation of emergency resources, unclear boundaries of cross-jurisdictional rescue responsibilities, local actors adopting a wait-and-see stance, and low engagement from social forces.

In recent years, global extreme climate events have become frequent, and both the frequency and severity of natural disasters have shown a marked upward trend, posing a severe threat to regional economic and social development and the safety of people’s lives and property [1,2]. As one of China’s most open and economically dynamic regions, the Guangdong–Hong Kong–Macao Greater Bay Area faces compound risks such as typhoons, heavy rain, and floods due to its unique geographic location and high level of urbanization [3]. In cross-jurisdictional disaster governance practice, coordination among the central regulatory authorities, local regulatory authorities, and social forces is a key link for improving emergency response efficiency and reducing disaster losses [4]. However, because participating actors differ significantly in their interest demands, resource endowments, and risk-bearing capacities [5], strategic game behaviors commonly occur in disaster collaborative governance, and designing effective incentive and constraint mechanisms to promote multi-party cooperation has become an urgent theoretical and practical problem to solve.

Because participating actors differ markedly in their interest demands, resource endowments, and risk-bearing capacities, strategic game behaviors commonly occur in the process of collaborative disaster governance [6]. In multi-actor disaster response scenarios, regulatory authorities and departments pursue maximization of public safety and

social stability [7], enterprises focus on balancing the costs and benefits of participating in relief efforts, and social organizations are constrained by their own resources and reputation incentives; the parties thus form complex strategic interactions around core issues such as responsibility sharing, resource allocation, and benefit distribution [8]. This heterogeneity of interests means no single actor has sufficient motivation for proactive cooperation, so free-riding and wait-and-see strategies easily become rational short-term choices, leading collaborative disaster governance into a collective action dilemma [9,10]. Therefore, how to design effective incentive and constraint mechanisms to promote multilateral cooperation—so that each participant can pursue its own utility maximization while achieving a Pareto improvement in overall social welfare—has become an urgent theoretical and practical problem in the field of collaborative disaster governance [11].

Evolutionary game theory, as an important tool for analyzing the strategy evolution of boundedly rational agents in dynamic interactions, has been widely applied in public governance, emergency management, and supply chain coordination [12–14]. Compared with the full-rationality assumption in classical game theory, evolutionary game theory acknowledges participants' bounded rationality and characterizes the evolution of population strategies through replicator dynamic equations [15], enabling a more realistic reflection of the dynamic features of multi-agent interactions in real society [16,17]. In disaster governance research, some scholars have constructed bilateral or multilateral evolutionary game models such as regulatory authorities-enterprise and regulatory authorities-social-organization interactions to analyze agents' strategy choices and their stability conditions under different scenarios. These studies provide a useful theoretical perspective for understanding cooperation dilemmas in disaster governance [18,19]. Evolutionary game theory, as an important tool for analyzing the strategy evolution of boundedly rational agents in dynamic interactions, has been widely applied in public governance, emergency management, and supply chain coordination [20]. The theory breaks through the full-rationality premise of classical game theory and, through core concepts such as replicator dynamics and evolutionarily stable strategies [21,22], describes the dynamic process by which participants, under conditions of incomplete information, gradually approach equilibrium via imitation learning and trial-and-error adjustments, thereby more closely matching the actual conditions of multi-agent strategic interactions in real society [23,24]. In the field of public governance, evolutionary game methods have been used to analyze the strategy evolution paths among regulatory authorities, market actors, and the public regarding policy implementation and compliance behavior [25–27]. In emergency management, scholars have applied this approach to explore the mobilization and coordination mechanisms of emergency collaboration among regulatory authorities, rescue forces, social emergency organizations, and supporting institutions. In supply chain coordination, evolutionary game models have been used to reveal the cooperation evolution rules and their stability conditions among diverse actors such as suppliers, manufacturers, and retailers under risk environments [28,29]. Participants' payoff structures thereby drive the system to evolve toward an ideal equilibrium state [30,31]. However, reward-and-punishment mechanisms in traditional studies are mostly set statically, meaning the intensity of punishment and the magnitude of rewards remain unchanged throughout the game process. This static mechanism faces obvious limitations in practice: when participants' violations are minor, overly severe punishment may provoke resistance; when violations are serious, fixed punishment intensity may be insufficient to produce effective deterrence [32–34]. Therefore, how to construct dynamically adjustable reward-and-punishment mechanisms to adapt to governance needs at different stages has become an important direction of current research [35].

In terms of incentive mechanism design, reward-and-punishment mechanisms play an important role in guiding participants to choose cooperative strategies [36–38]. Existing

studies indicate that regulatory authorities can effectively alter the payoff structures of game participants through positive incentives such as subsidies and tax relief and negative constraints such as fines and accountability, thereby driving the system to evolve toward an ideal equilibrium state [39–41]. In cooperation on emergency material reserves, supervision and punishment exceeding a critical threshold can suppress opportunistic behavior and enhance willingness to cooperate, while the synergistic effects of multiple incentive policies—such as one-time subsidies, revenue sharing, and cost subsidies—can promote the system toward a cooperative equilibrium [42]. In the field of safety production regulation, reasonably designed fine intensity has a positive promoting effect on regulatory authorities' guidance, and increases in policy subsidies and employee rewards positively drive enterprises to implement safety management [43]. In PPP large infrastructure projects, reasonable benefit distribution and a strong punishment mechanism are key factors in promoting multilateral cooperation [44]. In marine oil spill emergency cooperation, the strength of regulatory authorities' reward-and-punishment mechanisms directly affects the cooperation tendency of port enterprises and professional cleanup units [45]. Existing research shows that regulatory authorities can effectively change the game. From the existing literature, tripartite evolutionary game models have been widely applied in multi-agent collaborative governance studies [46]. In the field of emergency material reserves, some scholars constructed a tripartite game model of the regulatory authorities, material manufacturers, and logistics firms to analyze the impact of dynamic reward-and-punishment measures under a blockchain platform on firms' compliance behavior [47]. In safety production supervision, related research built a tripartite evolutionary game model of regulatory authorities, regulatory departments, chemical enterprises, and employees, demonstrating the superiority of nonlinear dynamic punishment mechanisms in controlling system instability [48]. In the field of marine oil spill emergency cooperation, researchers used stochastic evolutionary game theory to establish an emergency cooperation model among local regulatory authorities, port enterprises, and professional pollution-cleanup units [49], revealing the direct effect of regulatory authorities' reward-and-punishment mechanisms on cooperation willingness. In joint fire governance, scholars focused on the game interaction between fire management departments and industry regulatory departments, exploring how the level of fire information sharing drives the formation of collaborative governance patterns [50]. These studies validate the effectiveness of evolutionary game methods in analyzing multi-agent collaborative governance issues across different application scenarios.

However, existing research still has the following shortcomings. First, in terms of research subjects, studies on evolutionary games for cross-regional disaster collaborative governance are relatively scarce, especially lacking systematic analysis of the Guangdong–Hong Kong–Macao Greater Bay Area, a region with unique institutional contexts and governance structures. Second, in mechanism design, most studies consider only static reward-and-punishment mechanisms or a single linear dynamic mechanism, and do not sufficiently reveal the interaction mechanisms between dynamic reward-and-punishment mechanisms and multi-agent strategy evolution. Third, in model construction, some studies overlook how real-world constraints such as information asymmetry and agent heterogeneity in disaster governance affect game equilibria.

Based on the foregoing analysis, this paper, grounded in the practical needs of disaster collaborative governance in the Guangdong–Hong Kong–Macao Greater Bay Area, constructs a tripartite evolutionary game model among the central regulatory authorities, local regulatory authorities, and social forces, introduces a dynamic reward-and-punishment mechanism to characterize how punishment severity and reward magnitude dynamically adjust with the degree of actors' behavioral deviation, and systematically analyzes the strategy evolution paths and system stability conditions of the participating

actors. Through numerical simulation, it explores the influence of key parameters on game equilibria, providing theoretical support and decision-making reference for improving the institutional design of disaster collaborative governance in the Guangdong–Hong Kong–Macao Greater Bay Area. The theoretical contribution of this study lies in embedding a dynamic reward-and-punishment mechanism into the tripartite evolutionary game framework for cross-regional disaster collaborative governance, extending the application boundary of evolutionary game theory in the field of regional disaster governance, and offering an operational analytical paradigm for designing dynamic incentive mechanisms.

2. Materials and Methods

2.1. Game Subjects and Strategy Settings

This research constructs a tripartite evolutionary game model composed of the regional coordinating regulatory authorities G , local emergency management entities L , and social participation entities S . All three types of actors are boundedly rational, aim to maximize their expected payoffs, and adjust their next-period strategy choices based on the previous period's strategy payoffs.

The regional coordinating regulatory authorities, G , refer to the Greater Bay Area emergency coordination agency, superior coordination departments, or regulatory authority entities assuming cross-region overall functions supported by the central regulatory authorities; its strategy set is {actively promote, passively promote}. As Guangdong, Hong Kong, and Macao operate under distinct legal, administrative, and fiscal systems under “one country, two systems,” G is not treated as a single existing statutory body with binding cross-jurisdictional enforcement power. G is modeled as a composite, largely functional actor: in practice it corresponds to the coordination role played jointly by mainland central regulatory authorities. Let the probability that G chooses to actively promote be x and the probability of choosing to passively promote be $1 - x$. The local emergency management subject L includes relevant cities in Guangdong, Hong Kong, Macao and their meteorological, water, transportation, fire rescue, medical treatment and urban operation departments. These departments differ across the three jurisdictions in emergency-management structure, legal authority, and operational capacity; L aggregates them into a single representative actor as a deliberate simplification for tractability, not because their behavior is assumed to be homogeneous. Its strategy set is {actively coordinate, passively coordinate}. Let the probability that L chooses to actively coordinate be y and the probability of choosing to passively coordinate be $1 - y$. The social participation subject S includes enterprises, platform organizations, community organizations, volunteer rescue forces, infrastructure operators and the public. These groups differ substantially in interests, resource endowments, and participation capacity; S is likewise treated as a single representative actor for tractability. Its strategy set is {actively participate, passively participate}. Throughout the paper, x , y , z denote the population-level proportion of each actor group observed to be adopting the active strategy at a given time (equivalently, in the replicator-dynamics interpretation, the probability that a representative member of that group selects the active strategy); they are not direct measures of compliance rates or reported participation levels, although Section 4 discusses observable indicators that could proxy for them in practice. Let the probability that S chooses to actively participate be z and the probability of choosing to passively participate be $1 - z$.

To prevent the model's meaning from diverging, this paper imposes the following limits on the three types of strategies. The regional coordinating regulatory authorities' “active promotion” is not ordinary administrative publicity but refers to proactively establishing joint consultations, cross-jurisdictional early warning, resource allocation, performance evaluation, and liability recovery rules; “passive promotion” means maintaining minimal duty and information reception but not proactively bearing cross-

jurisdictional coordination costs. The local emergency management entity's "proactive coordination" emphasizes pre-disaster information sharing, joint assessment, prepositioning of supplies and teams, mutual dispatch during disasters, and collaborative post-disaster recovery; "passive coordination" is not complete inaction but only low-intensity cooperation under superior orders or disaster pressure. The social participation entity's "active participation" means platform companies, infrastructure operators, community organizations, and volunteer forces entering a normalized emergency network; "passive participation" refers to only the minimum compliant response. The above definitions focus the model on cross-jurisdictional coordination incentives rather than general disaster governance performance evaluation.

2.2. Model Logic and Benefit Flows

The core contradiction of the model is the mismatch between benefit spillover and cost internalization. When local actors and social actors actively collaborate, the reduced disaster losses and benefits, B_1 , B_2 , B_3 , are distributed among the three parties. However, the costs of active collaboration, C_l , C_s , are first borne by the local and social actors. When the regional coordinating regulatory authorities actively promote coordination, they can obtain superior support, R_g , and some aggregated benefits, but it must also bear coordination costs, C_g , and pay rewards to the local and social actors, R_l , R_s . If the local actor or the social actor adopts a passive strategy, the regional coordinating regulatory authorities can impose punishments, P_l , P_s , and passive behavior will cause additional losses, L_l , L_s . If the regional coordinating regulatory authorities are passive, the lack of cross-regional coordination will produce losses, L_g .

Two clarifications on the nature of these reward-and-punishment terms are needed before proceeding to the payoff matrix. First, R_l , R_s , P_l , P_s are not assumed to be purely cash transfers: depending on the instrument, they may take the form of fiscal subsidies, performance-linked transfer payments, or non-fiscal instruments such as reputational recognition, administrative penalties (e.g., point deductions, access restrictions), or legal liability recovery. The payoff matrix in Table 1 should accordingly be read as tracking each actor's net utility rather than a single homogeneous monetary quantity; private benefits (e.g., subsidies received by L or S), transfer payments between actors (e.g., R_l , R_s paid by G), and social welfare benefits (B_1 , B_2 , B_3 , E) are conceptually distinct even though they enter each actor's payoff additively; a penalty received by G is a private gain to G and a private loss to the paying actor, and does not by itself represent a net gain in social welfare. Second, treating R_l , R_s as revenue directly retained by G creates a potential perverse incentive noted by reviewers: G could in principle benefit financially from noncompliance by L and S , which would blunt rather than reinforce the incentive for G to sustain active coordination. To avoid this, R_l , R_s in this model should be interpreted as revenue that is earmarked—for example, returned as transfer payments into a dedicated regional emergency contingency fund, used to finance liability recovery for affected parties, or rebated toward future rewards—rather than accruing to G 's general operating budget. Under this earmarking assumption, the net effect of R_l , R_s on G 's incentive to promote is smaller than the raw payoff matrix in Table 1 suggests. Sections 4 and 6 revisit this point when discussing the regulatory authorities' payoff structure and budget constraints, and readers should treat the magnitude of G 's reported terminal promotion probability in Section 4 with this caveat in mind.

Therefore, the payoff matrix in this paper does not simply compare the total payoffs of "cooperation" versus "non-cooperation," but depicts the threefold tensions faced by the three types of actors in cross-border collaboration: (1) local and societal actors bear coordination costs while some benefits spill over; (2) the regional coordinating regulatory authorities must both provide incentives and bear institutional coordination costs; (3)

punishment can correct passive behavior, but without dynamic matching it can produce high-pressure inefficiency or incentive dependency. The subsequent dynamic reward–punishment functions are developed around these three tensions.

Table 1. Model Parameters and Meanings.

Parameter	Meaning	Constraint
C_g	Cost for regional coordinating regulatory authorities to promote coordination, including joint consultations, platform maintenance, cross-jurisdictional deployment, supervision and evaluation	$C_g \geq 0$
C_{g0}	Minimum standby and basic governance cost that the regional coordinating regulatory authorities must bear when passively promoting	$C_{g0} \geq 0$
C_l	Cost for local emergency management entities to actively collaborate, including information sharing, prepositioning of teams, interdepartmental communication and resource allocation	$C_l \geq 0$
C_s	Cost for social participation entities to participate actively, including organization and mobilization, operational adjustments, personnel deployment and information disclosure	$C_s \geq 0$
R_g	Support reward provided to the regional coordinating regulatory authorities by higher-level regulatory authorities or society	$R_g \geq 0$
R_l	Rewards, subsidies, or performance gains obtained when local entities actively cooperate	$R_l \geq 0$
R_s	Rewards, subsidies, or reputational benefits obtained when social participation entities participate actively	$R_s \geq 0$
P_l	Liability constraints, point deductions or recourse penalties imposed when local entities cooperate passively	$P_l \geq 0$
P_s	Credit constraints, penalties or access restrictions imposed when social participation entities participate passively	$P_s \geq 0$
B_1	Reduction in direct disaster losses generated only when local entities actively cooperate	$B_1 \geq 0$
B_2	Reduction in indirect disaster losses generated only when social entities participate actively	$B_2 \geq 0$
B_3	Reduction in combined losses when both local and social actors are proactive	$B_3 > B_1, B_2$
E	Societal benefits and resilience from tripartite collaboration	$E \geq 0$
L_g	Losses from lack of cross-border coordination caused by the regional coordinating regulatory authorities' passive promotion	$L_g \geq 0$
L_l	Emergency response delay, resource misallocation, and accountability losses caused by the local actors' passive collaboration	$L_l \geq 0$
L_s	Losses from information gaps, operational interruptions, and slow recovery due to the social actors' passive participation	$L_s \geq 0$
ω_g	Regional coordinating regulatory authorities' share of disaster loss reduction benefits	$0 \leq \omega_g \leq 1$
ω_l	Proportion of disaster loss reduction benefits allocated to local actors	$0 \leq \omega_l \leq 1$
ω_s	Proportion of disaster loss reduction benefits allocated to social actors	$0 \leq \omega_s \leq 1$
λ_g	Proportion of societal comprehensive benefits allocated to the regional coordinating regulatory authorities	$0 \leq \lambda_g \leq 1$
λ_l	Proportion of societal comprehensive benefits allocated to local actors	$0 \leq \lambda_l \leq 1$
λ_s	Proportion of societal comprehensive benefits allocated to social actors	$0 \leq \lambda_s \leq 1$
μ_l	Local actors' dynamic reward coefficient, reflecting increasing reward intensity as proactive collaboration performance improves	$\mu_l \geq 0$
μ_s	Social actors' dynamic reward coefficient, reflecting increasing reward intensity as active participation performance improves	$\mu_s \geq 0$

θ_l	Local actors' dynamic punishment coefficient, reflecting increasing punishment intensity as passive collaboration increases	$\theta_l \geq 0$
θ_s	Social actors' dynamic punishment coefficient, reflecting increasing punishment intensity as passive participation increases	$\theta_s \geq 0$

2.3. Basic Assumptions

Assumption 1. All three parties are boundedly rational actors who cannot fully grasp all information about others at the initial stage but can adjust strategies based on historical payoffs and current feedback.

Assumption 2. Disaster risks have spillover effects. Passive coordination by local actors or passive participation by social actors not only affects their own payoffs but also enlarges overall regional disaster losses.

Assumption 3. The regional coordinating regulatory authorities must incur institutional-building, platform-building, joint-drill, supervision and evaluation, and cross-border coordination costs to actively promote collaborative governance; if collaborative governance performs well, it can obtain higher-level policy support, reputation gains, and reduced disaster-loss benefits.

Assumption 4. Local emergency management actors must incur information-sharing, cross-department communication, resource allocation, personnel deployment, and liability-bearing costs to proactively coordinate; if they actively coordinate, they can obtain fiscal subsidies, performance rewards, reputation gains, and reduced disaster-loss benefits.

Assumption 5. Social participation actors must incur organization, time, funding, operational adjustment, or information-disclosure costs to participate actively; if they do, they can obtain subsidies, brand reputation, risk reduction, and public-safety benefits.

Assumption 6. The regional coordinating regulatory authorities can impose rewards or punishments based on the behaviors of local and social actors. The reward-and-punishment mechanism can be static or dynamically adjusted with coordination level, risk level, and governance performance. Because policy makers cannot directly observe the strategy probabilities x , y , z themselves, operationalizing this mechanism requires measurable proxy indicators rather than the probabilities as such.

2.4. Framework of Actor Relationships

Based on the above actor definitions and basic assumptions, the strategic interaction among the three parties is shown in Figure 1. The regional coordinating regulatory authorities influence local actors and social actors through cross-regional coordination, rewards, and punishments; local actors affect direct disaster loss control through proactive or passive coordination; social actors affect grassroots mobilization, operational continuity, and post-disaster recovery efficiency through active or passive participation. There is a complementary effect between local actors and social actors: actions by local departments alone may lack grassroots information and social resources; involvement of social forces alone also struggles to overcome cross-institutional resource scheduling constraints. Only when regional coordinating regulatory authorities continuously promote, local actors proactively coordinate, and social actors actively participate simultaneously can the system possibly form a stable high-collaboration pattern.

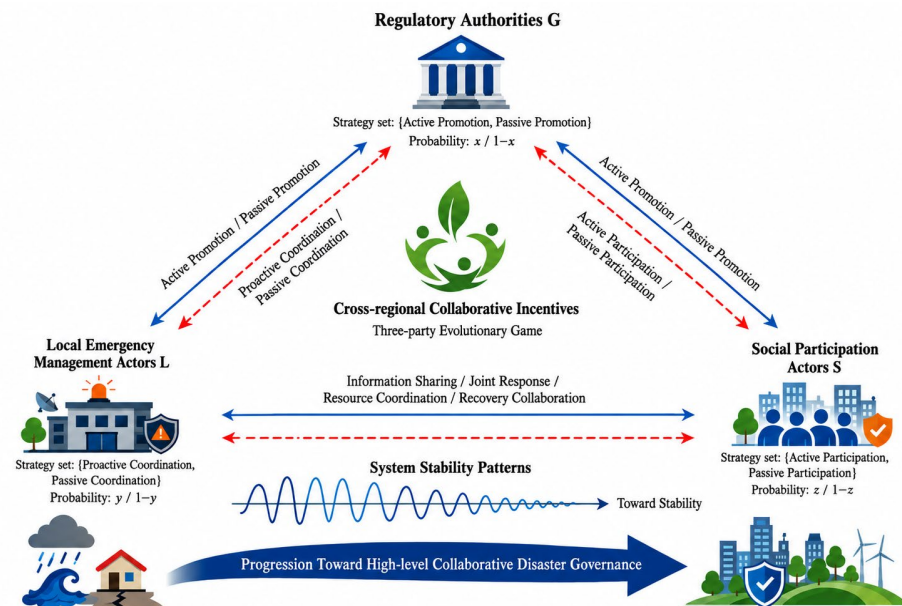


Figure 1. Framework of the Three-party Evolutionary Game for Disaster Collaborative Governance in the Greater Bay Area.

2.5. Parameter Settings

Where the benefit allocation ratios satisfy $\omega_g + \omega_l + \omega_s = 1$ and the comprehensive benefit allocation ratios satisfy $\lambda_g + \lambda_l + \lambda_s = 1$. Here, R_l, R_s, P_l, P_s are regarded as policy variables that can be adjusted by static or dynamic mechanisms, so their specific value is further elaborated in the section where the reward-and-punishment mechanism is embedded.

The disaster loss reduction benefit function is defined as follows:

$$B(y, z) = B_3 yz + B_1 y(1 - z) + B_2 (1 - y)z. \quad (1)$$

When all three parties adopt proactive strategies, a comprehensive social benefit E is generated and is allocated among the three parties according to $\lambda_g, \lambda_l, \lambda_s$.

2.6. Payoff Matrix

In Table 2, G_1 denotes regional coordinating regulatory authorities actively promoting, G_0 denotes passively promoting; L_1 denotes local actors proactively cooperating, L_0 denotes passively cooperating; S_1 denotes social actors actively participating, S_0 denotes passively participating.

Table 2. Payoff matrix for a three-player evolutionary game.

No.	Strategy Combination	U_G	U_L	U_S
1	(G_1, L_1, S_1)	$R_g - C_g - R_l - R_s + \omega_g B_3 + \lambda_g E$	$R_l - C_l + \omega_l B_3 + \lambda_l E$	$R_s - C_s + \omega_s B_3 + \lambda_s E$
2	(G_1, L_1, S_0)	$R_g - C_g - R_l + P_s + \omega_g B_1$	$R_l - C_l + \omega_l B_1$	$-P_s - L_s$
3	(G_1, L_0, S_1)	$R_g - C_g - R_s + P_l + \omega_g B_2$	$-P_l - L_l$	$R_s - C_s + \omega_s B_2$
4	(G_1, L_0, S_0)	$R_g - C_g + P_l + P_s$	$-P_l - L_l$	$-P_s - L_s$
5	(G_0, L_1, S_1)	$-C_{g0} - L_g + \omega_g B_3$	$-C_l + \omega_l B_3$	$-C_s + \omega_s B_3$
6	(G_0, L_1, S_0)	$-C_{g0} - L_g + \omega_g B_1$	$-C_l + \omega_l B_1$	$-L_s$
7	(G_0, L_0, S_1)	$-C_{g0} - L_g + \omega_g B_2$	$-L_l$	$-C_s + \omega_s B_2$
8	(G_0, L_0, S_0)	$-C_{g0} - L_g$	$-L_l$	$-L_s$

3. Model Solution

3.1. Expected Benefits

The regional coordinating regulatory authorities' expected benefits from choosing proactive promotion and passive promotion are, respectively, as follows:

$$U_G^1 = yz(R_g - C_g - R_l - R_s + \omega_g B_3 + \lambda_g E) + y(1 - z)(R_g - C_g - R_l + P_s + \omega_g B_1) + (1 - y)z(R_g - C_g - R_s + P_l + \omega_g B_2) + (1 - y)(1 - z)(R_g - C_g + P_l + P_s), \quad (2)$$

$$U_G^0 = yz(-C_{g0} - L_g + \omega_g B_3) + y(1 - z)(-C_{g0} - L_g + \omega_g B_1) + (1 - y)z(-C_{g0} - L_g + \omega_g B_2) + (1 - y)(1 - z)(-C_{g0} - L_g). \quad (3)$$

The local emergency management actor's expected benefits from choosing active collaboration and passive collaboration are, respectively, as follows:

$$U_L^1 = xz(R_l - C_l + \omega_l B_3 + \lambda_l E) + x(1 - z)(R_l - C_l + \omega_l B_1) + (1 - x)z(-C_l + \omega_l B_3) + (1 - x)(1 - z)(-C_l + \omega_l B_1), \quad (4)$$

$$U_L^0 = xz(-P_l - L_l) + x(1 - z)(-P_l - L_l) + (1 - x)z(-L_l) + (1 - x)(1 - z)(-L_l). \quad (5)$$

The social participation actor's expected benefits from choosing active participation and passive participation are, respectively, as follows:

$$U_S^1 = xy(R_s - C_s + \omega_s B_3 + \lambda_s E) + x(1 - y)(R_s - C_s + \omega_s B_2) + (1 - x)y(-C_s + \omega_s B_3) + (1 - x)(1 - y)(-C_s + \omega_s B_2), \quad (6)$$

$$U_S^0 = xy(-P_s - L_s) + x(1 - y)(-P_s - L_s) + (1 - x)y(-L_s) + (1 - x)(1 - y)(-L_s). \quad (7)$$

3.2. Replicator Dynamic Equation

The average expected payoffs of the three subjects are as follows:

$$\bar{U}_G = xU_G^1 + (1 - x)U_G^0, \bar{U}_L = yU_L^1 + (1 - y)U_L^0, \bar{U}_S = zU_S^1 + (1 - z)U_S^0. \quad (8)$$

Accordingly, the replicator dynamic equations are obtained:

$$F(x) = \frac{dx}{dt} = x(1 - x)(U_G^1 - U_G^0), \quad (9)$$

$$F(y) = \frac{dy}{dt} = y(1 - y)(U_L^1 - U_L^0), \quad (10)$$

$$F(z) = \frac{dz}{dt} = z(1 - z)(U_S^1 - U_S^0). \quad (11)$$

From Equations (9)–(11), the evolutionary direction of each party's strategy is determined by the payoff differences between the two strategies. If $U_G^1 > U_G^0$, the regional coordinating regulatory authorities' probability of choosing active promotion increases; if $U_L^1 > U_L^0$, the local actors' probability of choosing proactive collaboration increases; if $U_S^1 > U_S^0$, the social actors' probability of choosing active participation increases.

3.3. Analysis of the Stability of the Three Parties

To clearly determine the evolutionary directions of the three parties' strategies, the following is established:

$$\Delta_G = U_G^1 - U_G^0, \Delta_L = U_L^1 - U_L^0, \Delta_S = U_S^1 - U_S^0.$$

From Equations (2)–(7), we obtain the following:

$$\Delta_G = R_g - C_g + C_{g0} + L_g + P_l(1 - y) + P_s(1 - z) - R_ly - R_sz + \lambda_g Eyz, \quad (12)$$

$$\Delta_L = L_l - C_l + x(R_l + P_l) + \omega_l[B_1(1 - z) + B_3z] + \lambda_l Exz, \quad (13)$$

$$\Delta_S = L_S - C_S + x(R_S + P_S) + \omega_s[B_2(1 - y) + B_3y] + \lambda_s Exy. \quad (14)$$

Equation (12) indicates that whether the regional coordinating regulatory authorities continues to promote depends mainly on the relative magnitudes of higher-level support, baseline loss pressure, and reward expenditures; Equation (13) indicates that local actors' proactive coordination is influenced not only by rewards and punishments, but also by the level of social actors' participation Z ; Equation (14) indicates that active participation by social actors likewise depends on the local actors' coordination level y . This shows that cross-border disaster governance is not a unilateral incentive issue but a typical complementary coordination problem.

3.3.1. Stability of the Regional Coordination Regulatory Authorities

From $F(x) = x(1 - x)\Delta_G$ we know the following:

$$\frac{\partial F(x)}{\partial x} = (1 - 2x)\Delta_G \quad (15)$$

When $\Delta_G > 0$, $x = 1$ is a stable strategy and $x = 0$ is an unstable strategy; when $\Delta_G < 0$, $x = 0$ is a stable strategy and $x = 1$ is an unstable strategy. Further, the threshold of superior support required for the regional coordination regulatory authorities to choose proactive promotion can be obtained as follows:

$$R_g^*(y, z) = C_g - C_{g0} - L_g - P_l(1 - y) - P_s(1 - z) + R_ly + R_sy - \lambda_g Eyz. \quad (16)$$

Proposition 1. Under the given condition of y, z , if $R_g > R_g^*(y, z)$, the regional coordination regulatory authorities' strategy evolves toward proactive promotion; if $R_g < R_g^*(y, z)$, the regional coordination authorities' strategy evolves toward passive promotion.

Proposition 1 indicates that the regional coordination regulatory authorities' proactive promotion is not determined solely by accountability pressure. When local and social actors are both proactive, $\lambda_g Eyz$ can lower the threshold of superior support. However, if the proactiveness of local and social actors is insufficient, the regional coordination regulatory authorities still need to bear reward expenditures and coordination costs, and their willingness to promote may decline.

3.3.2. Stability of the Local Emergency Management Subject

From $F(y) = y(1 - y)\Delta_L$, we know that when $\Delta_L > 0$, $y = 1$ is the stable strategy; when $\Delta_L < 0$, $y = 0$ is the stable strategy. Under the condition of $R_l + P_l + \lambda_l Ez > 0$, the threshold probability of regional coordinating regulatory authorities' promotion required for the local subject to actively collaborate is as follows:

$$x_L^*(z) = \frac{C_l - L_l - \omega_l[B_1(1 - z) + B_3z]}{R_l + P_l + \lambda_l Ez}. \quad (17)$$

Proposition 2. Given z , if $x > x_L^*(z)$, the local emergency management subject's strategy evolves toward active collaboration; if $x < x_L^*(z)$, the local emergency management subject's strategy evolves toward passive collaboration.

Proposition 2 indicates that the local subject's active collaboration requires sustained promotion by the regional coordinating regulatory authorities but does not rely entirely on regulatory authorities' pressure. As the social actors' active participation level z increases, $\omega_l[B_1(1 - z) + B_3z]$ and $\lambda_l Ez$ increase, and the threshold for the local subject's active collaboration decreases, suggesting social participation can reduce local collaboration resistance through information supplementation, grassroots mobilization, and recovery cooperation.

3.3.3. Stability of the Social Participation Subject

From $F(z) = z(1 - z)\Delta_s$ it can be seen that when $\Delta_s > 0, z = 1$ is a stable strategy; when $\Delta_s < 0, z = 0$ is a stable strategy. Under the condition of $R_s + P_s + \lambda_s E y > 0$, the threshold probability of regional coordinating regulatory authorities required for active social participation is as follows:

$$x_s^*(y) = \frac{C_s - L_s - \omega_s[B_2(1 - y) + B_3y]}{R_s + P_s + \lambda_s E y}. \quad (18)$$

Proposition 3. *Under the given condition y , if $x > x_s^*(y)$, the strategy of the social participation subject evolves toward active participation; if $x < x_s^*(y)$, the strategy of the social participation subject evolves toward passive participation.*

Proposition 3 indicates that whether social subjects participate depends not only on subsidies or penalties but also on whether local actors provide clear coordination interfaces. As the proactive collaboration level of local actors y increases, social subjects can obtain more stable organizational entry points, information interfaces, and expected returns, and the participation threshold correspondingly decreases.

The key to stable tripartite collaboration is not the maximization of a single parameter, but forming a linked structure of “regulatory authorities-push-threshold decreases—local collaboration-threshold decreases—social participation-threshold decreases.” If rewards only increase the benefits of local or social actors without reducing the net burden on regional coordinating regulatory authorities, the system may experience a structural imbalance with active local and social actors but reduced regulatory authorities’ promotion; if penalties only raise the cost of passivity without collaborative benefit feedback, the system may show short-term responses and long-term relapse. Therefore, when comparing static, linear dynamic, and nonlinear dynamic reward-and-punishment mechanisms later, the emphasis is placed on whether they can simultaneously improve $\Delta_G, \Delta_L, \Delta_S$.

3.4. Embedding Different Reward-and-Punishment Mechanisms

To compare the stability control effects of the reward-and-punishment mechanisms, set the following mechanisms:

No reward or punishment:

$$R_l = R_s = P_l = P_s = 0 \quad (19)$$

Static reward and punishment: $R_l = R_{l0}, R_s = R_{s0}, P_l = P_{l0},$

$$P_s = P_{s0}; \quad (20)$$

Linear dynamic reward and punishment: $R_l(t) = R_{l0} + \mu_l y,$

$$R_s(t) = R_{s0} + \mu_s z, \quad (21)$$

$$P_l(t) = P_{l0} + \theta_l(1 - y), P_s(t) = P_{s0} + \theta_s(1 - z);$$

Nonlinear dynamic reward and punishment: $R_l(t) = R_{l0} + \mu_l x y^2 z,$

$$R_s(t) = R_{s0} + \mu_s x z^2 y \quad (22)$$

$$P_l(t) = P_{l0} + \theta_l x(1 - y)^2, P_s(t) = P_{s0} + \theta_s x(1 - z)^2.$$

Equation (21) indicates that rewards and punishments vary linearly with the agents’ strategy levels, featuring clear rules and easy operation but fixed marginal incentives and constraints. Equation (22) indicates that rewards depend not only on an agent’s own proactiveness but also on regional coordinated regulatory authorities’ promotion and another agent’s cooperation; punishments increase with the degree of passive behavior, able to suppress low-level compliance and free-riding.

3.5. Equilibrium Points and Stability Determination

Let $F(x) = F(y) = F(z) = 0$, the system has eight pure-strategy equilibrium points:

$$\begin{aligned} E_1 &= (0,0,0), E_2 = (0,0,1), E_3 = (0,1,0), E_4 = (0,1,1), \\ E_5 &= (1,0,0), E_6 = (1,0,1), E_7 = (1,1,0), E_8 = (1,1,1). \end{aligned} \quad (23)$$

Here, $E_8 = (1,1,1)$ denotes the regional coordinating regulatory authorities actively promoting, the local emergency management entity proactively collaborating, and the social participation entity actively participating—the ideal state this paper aims to achieve. $E_1 = (0,0,0)$ denotes all three parties adopting passive strategies, representing a failure of disaster collaborative governance.

The Jacobian matrix is constructed as follows:

$$J = \begin{bmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{bmatrix}. \quad (24)$$

If all three eigenvalues at an equilibrium point have negative real parts, the equilibrium is locally asymptotically stable; if at least one eigenvalue has a positive real part, the equilibrium is unstable.

Because each pure-strategy equilibrium lies at a corner of the unit cube (x, y, z each equal to 0 or 1), the terms $x(1-x)$, $y(1-y)$, $z(1-z)$ and their derivatives cause all off-diagonal entries of J to vanish identically at every one of the eight corners; this was verified symbolically (not merely assumed) for the no-mechanism, static, linear dynamic, and nonlinear mechanisms. Consequently, the three eigenvalues at a corner equal the diagonal entries themselves: $\lambda_x = \kappa(1-2x)\Delta G$, $\lambda_y = \kappa(1-2y)\Delta L$, $\lambda_z = \kappa(1-2z)\Delta S$, each evaluated at that corner. Applying this to all eight points under Table 3's benchmark parameters shows that, for the baseline nonlinear mechanism, none of the eight pure-strategy points is locally stable under all three conditions simultaneously.

Table 3. Simulation Parameter Values.

Parameter	Value	Basis for Assignment
C_{g0}	0.8	Regional coordinating regulatory authorities must bear institutional coordination costs such as cross-region consultations, platform maintenance, joint duty, and supervision and evaluation
C_g	0.8	Even under passive promotion, there remain minimal duty, information reception, and basic governance costs
C_l	8.0	Proactive local collaboration involves cross-institution communication, resource allocation, prepositioning teams, and assuming responsibilities, with costs higher than ordinary departmental cooperation
C_s	5.5	Social actors participating must bear organization and mobilization, operational adjustments, personnel deployment and information disclosure costs
R_g	2.2	Under the baseline scenario, superior-level support and reputation gains are limited and cannot fully cover regional coordination costs
R_l	2.0	Static basic reward for proactive coordination by local actors
R_s	1.6	Static basic reward for active participation by social actors
P_l	1.5	Static basic penalty for passive coordination by local actors
P_s	1.2	Static basic penalty for passive participation by social actors
B_1	6.7	Converted from the direct loss reduction between “Hato-Mangkhet,” representing the contribution of proactive local coordination to controlling direct losses

B_2	2.0	Converted from the indirect loss reduction between “Hato-Mangkhut,” representing the contribution of active social participation to controlling indirect losses
B_3	8.6	Converted from the total loss reduction between “Hato-Mangkhut,” representing the combined mitigation benefit when local and social actors are both actively engaged
E	4.6	Set based on cross-border impacts, population movements, and operational disruption pressures in the “Mangkhut” cases in Hong Kong and the mainland
L_g	3.0	Insufficient regional coordination leading to degraded early-warning linkage, resource integration, and post-disaster recovery efficiency
L_l	2.4	Passive local coordination causing delayed response, resource misallocation, and liability risks
L_s	1.5	Passive social participation causing information gaps, inadequate grassroots mobilization, and slow recovery
ω_g	0.4	Regional coordinating regulatory authorities’ share of disaster loss-reduction benefits
ω_l	0.35	Proportion of disaster loss-reduction benefits allocated to local actors
ω_s	0.25	Proportion of disaster loss-reduction benefits allocated to social actors
λ_g	0.3	Regional coordinating regulatory authorities’ share of social aggregate benefits
λ_l	0.3	Proportion of social aggregate benefits allocated to local actors
λ_s	0.4	Proportion of social comprehensive benefits allocated to social actors
μ_l	1.8	Local actor dynamic reward coefficient
μ_s	1.4	Social actor dynamic reward coefficient
θ_l	1.8,	Local actor dynamic penalty coefficient
θ_s	1.5	Social actor dynamic penalty coefficient
κ	0.18	Strategy adjustment speed, reflecting the gradual learning process under bounded rationality

Beyond the eight pure-strategy corners, the system may also admit an interior equilibrium where x, y, z all lie strictly between 0 and 1 and $\Delta G = \Delta L = \Delta S = 0$ simultaneously. A numerical root search (grid seeding plus local root-finding) finds exactly one interior equilibrium for the static, linear dynamic, and baseline nonlinear mechanisms under Table 3’s parameters, but none for the parameter-adjusted nonlinear mechanism. The system can settle near a genuinely mixed-strategy state instead of a pure corner. This interior equilibrium is generically only a saddle in a three-actor replicator system of this form (it is approached along some directions and repelled along others), so its practical relevance is that it slows convergence and creates path-dependence on initial conditions, not that it constitutes an alternative stable outcome. This distinguishes local asymptotic stability, verified above, from global convergence: a trajectory converging to a corner from one initial condition does not establish that the same corner attracts all initial conditions in the presence of an interior equilibrium or of other stable corners.

The oscillation reported under the linear dynamic mechanism can be attributed to complex eigenvalues of the Jacobian away from the pure-strategy corners rather than to the numerical solver: evaluating the Jacobian numerically over a grid of interior states under the linear mechanism’s parameters reveals a substantial region of the state space where the eigenvalues form a complex-conjugate pair with positive real part alongside one real, negative eigenvalue—a local spiral-saddle signature consistent with transient oscillatory adjustment before eventual convergence or divergence from that neighborhood. This is a structural property of how the linear reward-and-punishment terms couple x, y , and z (each actor’s payoff differential depends linearly on the other actors’ strategy shares).

At $E_8 = (1,1,1)$, the necessary directional conditions for system stability can be written as follows:

$$R_g - C_g - R_l - R_s + \lambda_g E + C_{g0} + L_g > 0, \quad (25)$$

$$R_l + P_l + L_l - C_l + \omega_l B_3 + \lambda_l E > 0, \quad (26)$$

$$R_s + P_s + L_s - C_s + \omega_s B_3 + \lambda_s E > 0. \quad (27)$$

Equation (25) indicates that if the reward expenditures borne by the regional coordinating regulatory authorities are too high while higher-level support is insufficient, their willingness to actively promote may decline; Equations (26) and (27) show that rewards, punishments, and expected risk losses all increase the probability that local and social actors choose active strategies.

4. Numerical Simulation

The key to parameter setting is not to mechanically plug real losses into the model, but to convert case facts into relative strengths. This paper selects “Hato” and “Mangkhut” as paired cases for loss reduction because both are typhoon disaster scenarios in the Greater Bay Area: “Hato” exposed shortcomings in warning, coordination, social mobilization, and recovery collaboration, while “Mangkhut” corresponds to stronger contingency preparation, cross-department duty arrangements, and social response. This pairing does not prove that all loss differences are caused by collaborative governance, but it provides an interpretable parameter scale for the claim that “improved collaboration will significantly reduce direct, indirect, and total losses.” This use of the two cases should be read with caution: the difference in reported losses between Hato and Mangkhut reflects differences in hazard intensity, storm track, rainfall timing, and infrastructure exposure in addition to any difference in collaborative governance quality, and the two events are not a controlled comparison. The parameters below are therefore treated as an interpretable ordinal scale motivated by these cases, not as an empirical estimate of the causal effect of governance on losses; Section 6 revisits this as a limitation.

Following nondimensionalization, this paper converts real disaster losses and case experience into relative parameters on a 0–10 scale. Accordingly, using “Hato” total loss as the severe-disaster baseline, the direct-loss reduction from proactive local collaboration, the indirect-loss reduction from active social participation, and the total-loss reduction from their combined effect are, respectively, converted into $B_1 = 6.7$ $B_2 = 2.0$ $B_3 = 8.6$.

“Mangkhut” produced destructive winds, record storm surge, numerous toppled trees, flight cancellations, and injuries, indicating that disaster impacts are not confined within administrative boundaries; multi-province mainland damage, emergency relocations, and direct economic loss data further indicate significant cross-regional resource pressure from typhoon disasters. Based on this, this paper sets the comprehensive resilience gain from tripartite collaboration as $E = 4.6$, and the losses caused by passive local collaboration, social negative participation, and insufficient regional coordination as $L_l = 2.4$ $L_s = 1.5$ $L_g = 3.0$. Collaboration costs, reward-and-punishment intensity, and superior-level support benefits are assigned relatively in light of institutional frictions in cross-institution coordination, joint duty, information sharing, resource dispatch, and responsibility recovery. These assignments are used to compare evolutionary directions under different reward-and-punishment mechanisms and do not represent direct monetary estimates of real economic losses.

4.1. Initial Simulation Under Benchmark Parameters

From Figures 2 and 3, under the case-calibrated benchmark parameters, the system does not automatically reach full tripartite coordination. The regional coordinating regulatory authorities, influenced by risk spillover, baseline loss pressures, and higher-level

support benefits, show a strong initial tendency to promote cooperation; however, the local emergency management actor and the social participation actor still face active coordination costs, mobilization costs, and benefit spillover issues, so their strategy probabilities rise more slowly than the regulatory authorities'. This result indicates that the coordination dilemma in disaster governance in the Greater Bay Area is not solely determined by whether the regulatory authorities push but arises from a mismatch of benefits among regulatory authorities' promotion, local responses, and social participation.

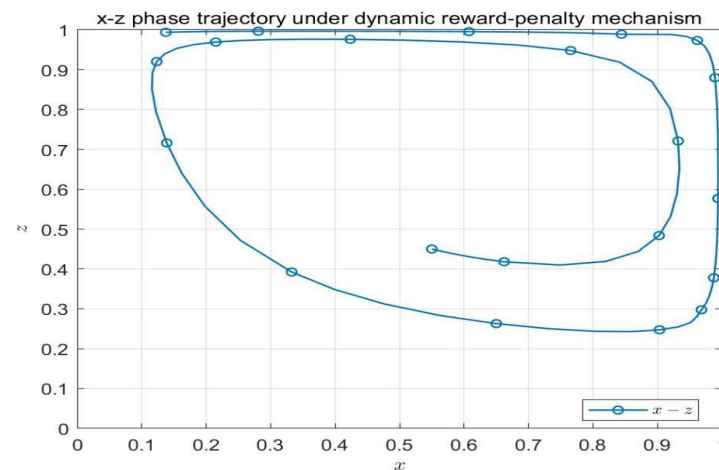


Figure 2. Phase-plane evolution of the three parties.

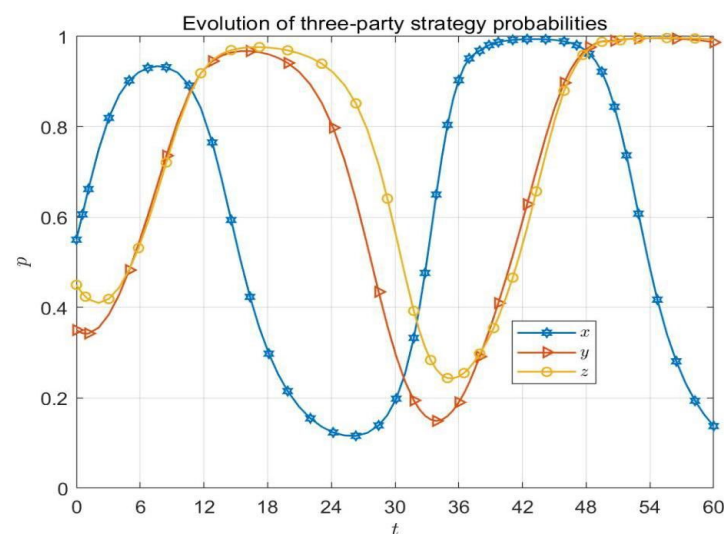


Figure 3. Time evolution of the three parties' strategies under the benchmark parameters.

4.2. Simulation Without Rewards and Penalties

Figures 4 and 5 indicate that, when no rewards or penalties are set, the regional coordinating regulatory authorities' probability of actively promoting eventually approaches 1, while the probabilities of active strategies for the local and social actors both decline to near 0, yielding an average coordination level of only 0.334. The reason is that the regulatory authorities still have incentives to promote in the face of cross-border risk spillovers and gaps in coordination, whereas local and social actors lack subsidies, performance benefits, liability recovery, or credit constraints, so the costs of proactive coordination cannot be adequately compensated. This produces a structural imbalance of "regulatory authorities actively promoting—local actors passively coordinating—society disengaged."

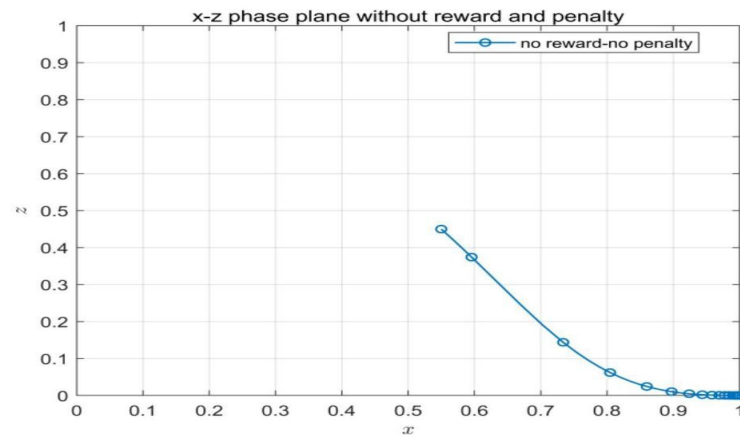


Figure 4. Phase-plane evolution of the three parties' x-z without rewards and penalties.

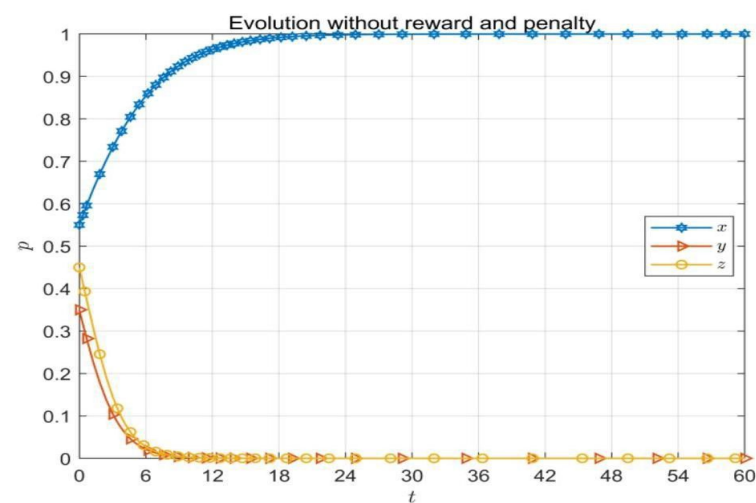


Figure 5. Temporal evolution of the three parties' strategies without rewards and penalties.

4.3. Linear Reward-and-Punishment Mechanism

To further identify the boundaries of different reward-and-punishment mechanisms, this paper examines five cases, respectively: static rewards, static punishments, static rewards with dynamic punishments, dynamic rewards with static punishments, and linear dynamic rewards with dynamic punishments. The comparison focuses not on whether any single actor's probability rises in the short term, but on whether the three parties' strategies can synchronously evolve toward a high-collaboration state.

4.3.1. Static Reward Sensitivity Simulation

Figures 6 and 7 reflect the impact of varying fixed reward intensity on system evolution. As static reward intensity increases, the probabilities of proactive strategies for local actors and social actors significantly rise in the early stage, indicating that fixed subsidies and performance rewards can alleviate the cost pressures of active collaboration. However, higher reward intensity also increases the financial burden on regional coordinating regulatory authorities, and if higher-level support is insufficient, the regulatory authorities' promotion probability may decline later. Therefore, static rewards can improve local behavior but are unlikely to alone sustain synchronized high collaboration among all three parties.

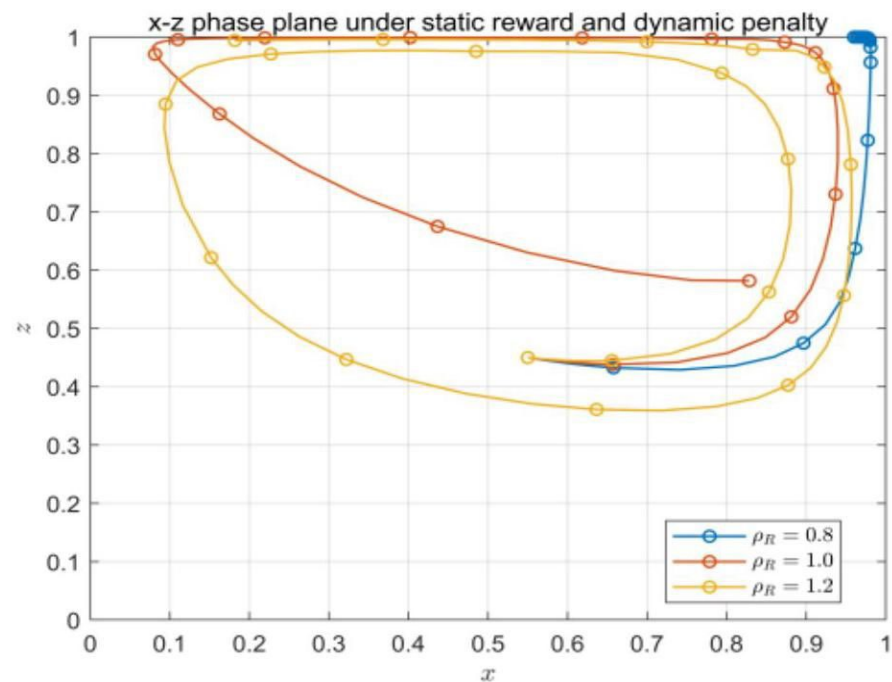


Figure 6. Phase-plane evolution of the three parties' x-z under changes in static reward intensity.

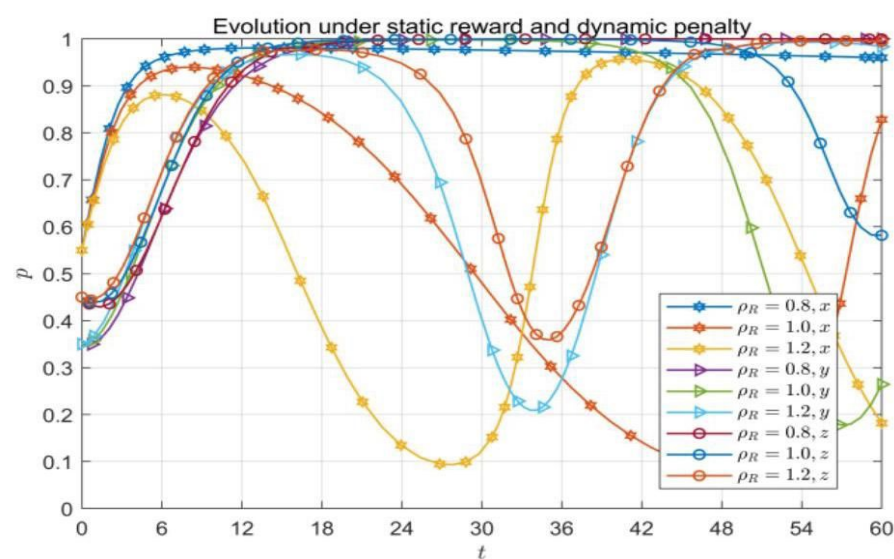


Figure 7. Time evolution of the three parties' strategies under changes in static reward intensity.

4.3.2. Static Punishment Sensitivity Simulation

Figures 8 and 9 show that after the static penalty intensity increases, the opportunity costs of passive local coordination and social disengagement rise, and the system is more likely to shift toward proactive strategies in the short term. Compared with static rewards, static penalties have a stronger corrective effect on low-collaboration states, but their problem is that the penalty standards are fixed and cannot distinguish disaster risk levels, differences in actors' capacities, or degrees of negative behavior. If penalties are designed too harshly, they may suppress social participation; if penalties are too weak, they cannot form a stable constraint.

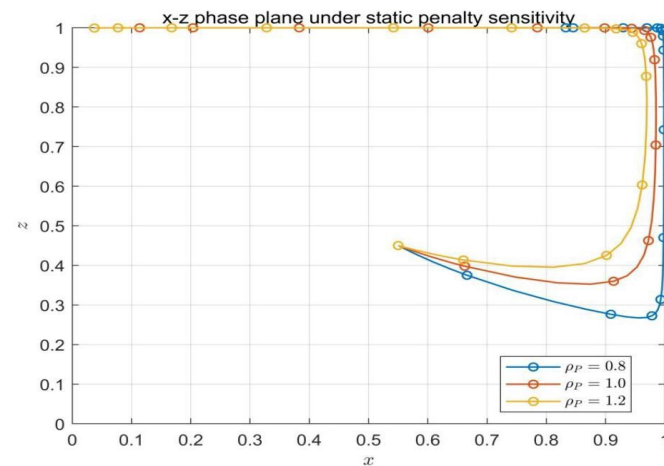


Figure 8. Phase-plane evolution of the three parties' x-z under changes in static penalty intensity.

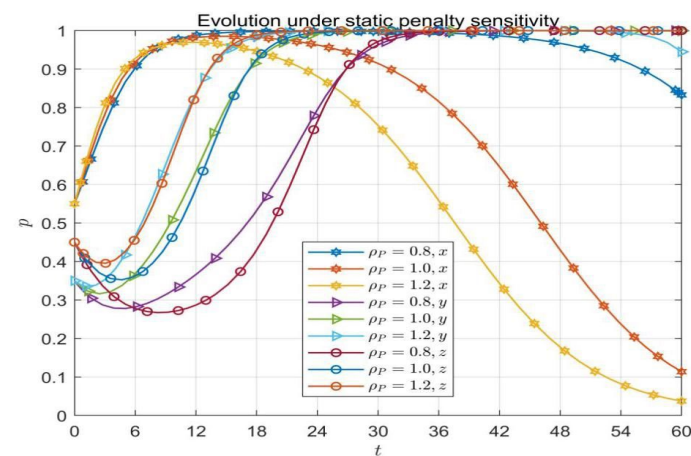


Figure 9. Time evolution of the three parties' strategies under changes in static penalty intensity.

4.3.3. Simulation of Static-Reward-and-Dynamic-Punishment Mechanism

Figures 10 and 11 indicate that under the static-reward-and-dynamic-punishment combination, the regional coordinating regulatory authorities can still maintain a relatively high promotion probability, with a terminal value of about 0.794; however, the local parties' proactive cooperation probability is only about 0.211, and the social parties' active participation probability is about 0.493, yielding an average cooperation level of about 0.499. This result shows that dynamic punishment can raise the cost of passive behavior but cannot fully offset the high cost of proactive cooperation for local parties; if rewards remain fixed, local parties tend to choose minimal compliance, and social participation is unlikely to become stably embedded in the cross-regional governance network.

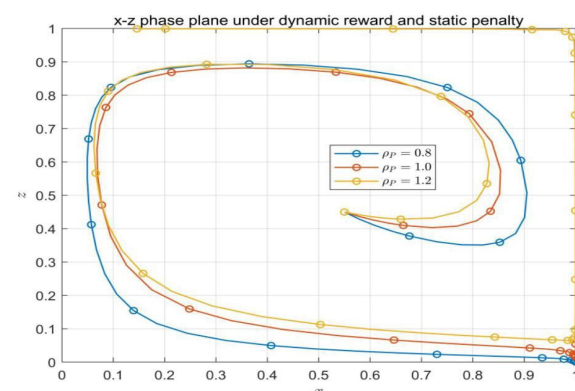


Figure 10. Phase-plane evolution of the three parties' x - z under the static-reward–dynamic-punishment mechanism.

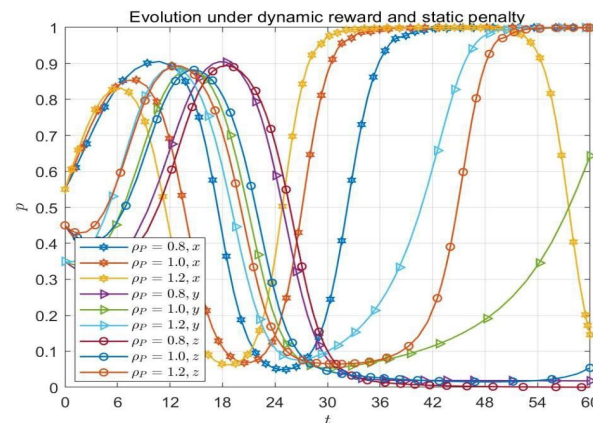


Figure 11. Temporal evolution of the three parties' strategies under the static-reward–dynamic-punishment mechanism.

4.3.4. Simulation of Dynamic-Reward-and-Static-Penalty Mechanism

Figures 12 and 13 show that dynamic rewards can significantly increase the regional coordinated regulatory authorities' probability of promoting collaboration and raise the local actors' probability of proactive collaboration to about 0.517; however, the social participants' final probability is only about 0.025, with an average collaboration level of roughly 0.514. The reason is that when rewards vary with proactive behavior, local actors receive clearer performance feedback, but static penalties lack progressive constraints on social actors' passive participation, so social forces may still withdraw due to input costs, unclear responsibilities, and unstable returns.

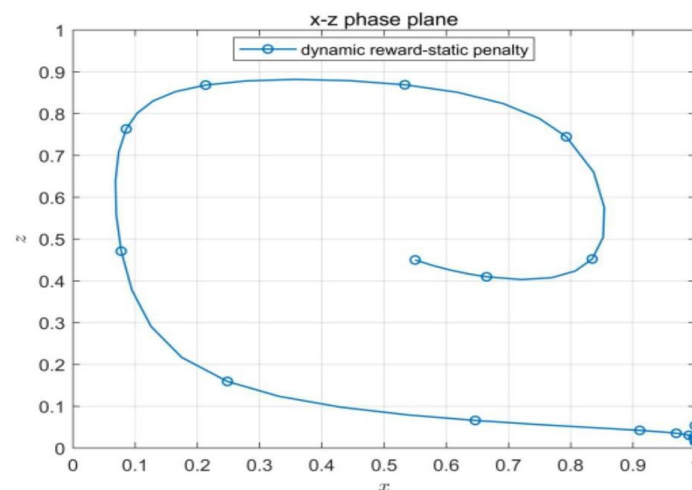


Figure 12. Phase-plane evolution of the three parties' x - z under the dynamic-reward–static-penalty mechanism.

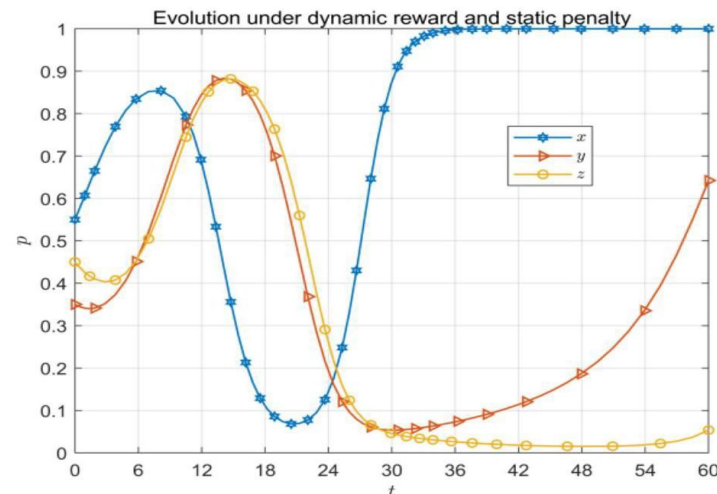


Figure 13. Time evolution of the three parties' strategies under the dynamic-reward–static-penalty mechanism.

4.3.5. Simulation of Linear Dynamic-Reward-and-Dynamic-Penalty Mechanisms

Figures 14 and 15 indicate that linear dynamic rewards and dynamic penalties can prompt adjustments in the three parties' strategies in the early stage, but the local and social actors still decline later, with terminal states of approximately 0.149 and 0.084, and an average collaboration level of about 0.411. This result suggests that although a simple linear mechanism is more flexible than a fully static one, its marginal incentives and marginal penalties are fixed and cannot fully capture the complementary gains among “regulatory authorities promotion-local coordination-social participation,” nor effectively address the high friction costs in cross-institutional, cross-departmental, and cross-platform coordination in the Greater Bay Area.

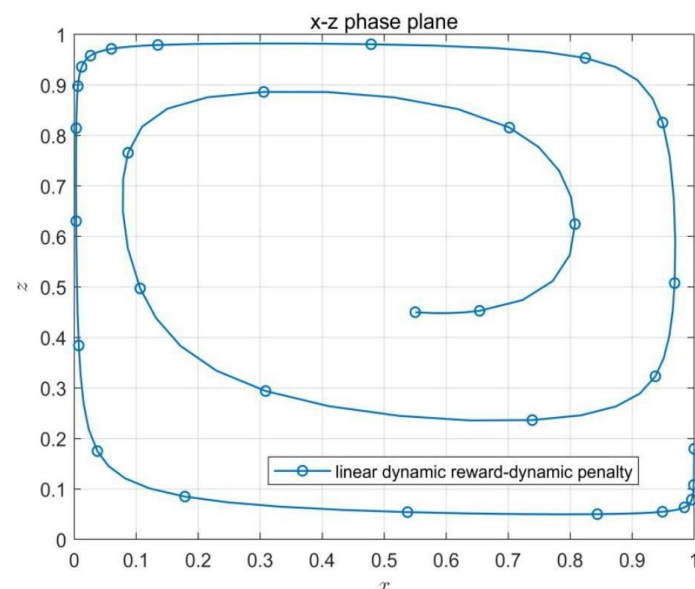


Figure 14. Evolution of the tripartite main x-z in the phase plane under the linear dynamic-reward–dynamic-penalty system.

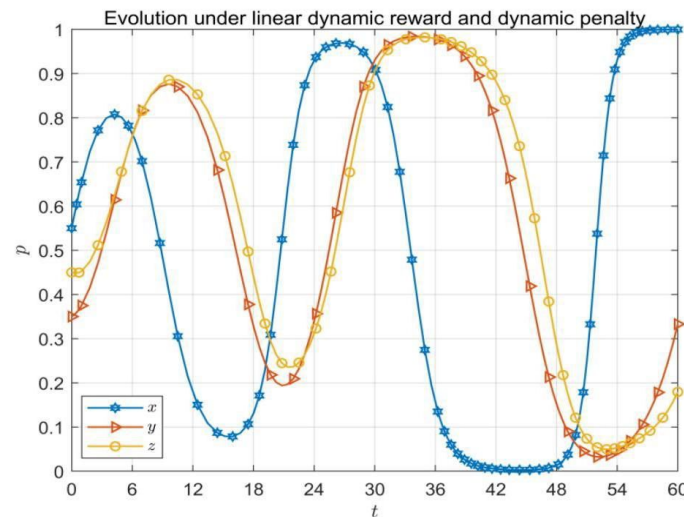


Figure 15. Temporal evolution of the tripartite strategies under the linear dynamic-reward-dynamic-penalty system.

4.4. Nonlinear Dynamic Reward-and-Penalty Mechanism and Its Optimization

The shortcoming of the linear mechanism is that marginal incentives and marginal constraints are fixed, making it difficult to reflect the real-world feature that higher cross-regional governance coordination yields stronger complementary gains. Therefore, this paper further introduces a nonlinear dynamic reward-and-penalty function, tying rewards to the tripartite complementary coordination performance and tying penalties to the degree of passivity under regional coordinating regulatory authorities' pressure.

Figures 16 and 17 show that the baseline nonlinear dynamic reward-and-penalty mechanism significantly improves the behavior of local and social actors, with their terminal state probabilities reaching approximately 0.996 and 0.998, respectively, and the average coordination level rising to about 0.718. Compared with the linear mechanism, the nonlinear reward ties local and social actors' payoffs to tripartite coordination performance, amplifying complementary co-benefits; the nonlinear penalty intensifies progressively with the degree of passivity, suppressing low-level compliance and free-riding. However, under the baseline parameters, the regional coordinating regulatory authorities' terminal state probability is only about 0.160, indicating that when reward expenditures and coordination costs are high while higher-level support is insufficient, regulatory authorities' willingness to promote may still decline.

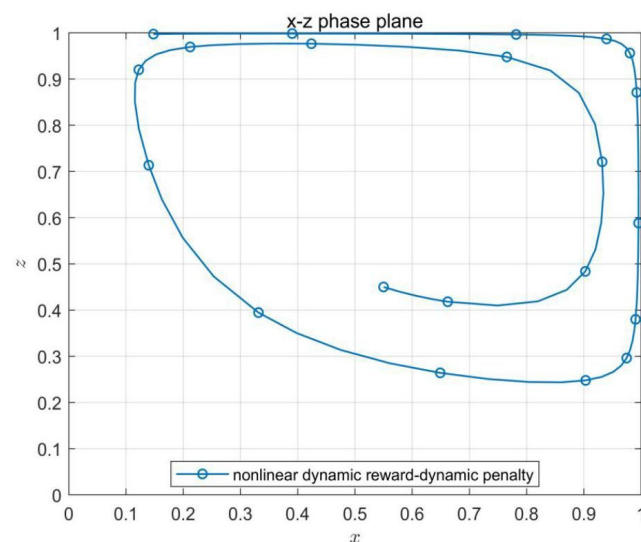


Figure 16. Phase-plane evolution of the three parties x-z under the baseline nonlinear dynamic reward-and-penalty mechanism.

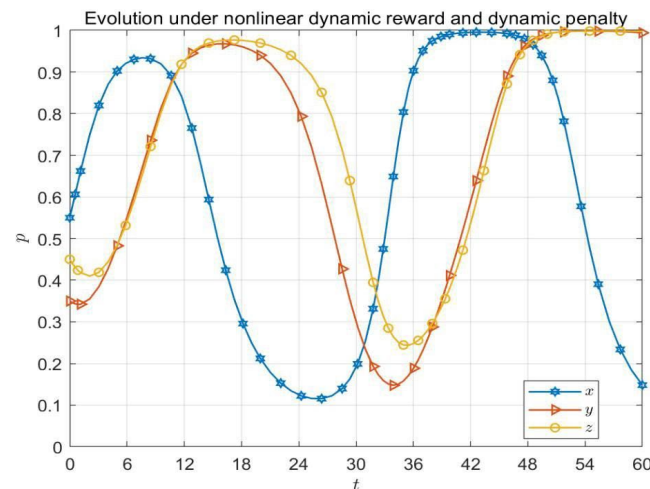


Figure 17. Time evolution of the three parties' strategies under the baseline nonlinear dynamic reward-and-penalty mechanism.

Parameter Tuning and Optimization of the Nonlinear Dynamic Reward-and-Penalty Mechanism

Figures 18–20 further indicate that the nonlinear dynamic reward-and-punishment mechanism can only drive the system to an ideal state when paired with stable superior support and moderate reward-and-punishment coefficients. After increasing the regional coordinating regulatory authorities' support benefit to 10.8 and adjusting the local reward coefficient, social reward coefficient, local punishment coefficient, and social punishment coefficient to 3.0, 2.4, 3.0, and 2.4, respectively, the terminal probabilities for all three parties reach about 0.999, and the average coordination level approaches 1.

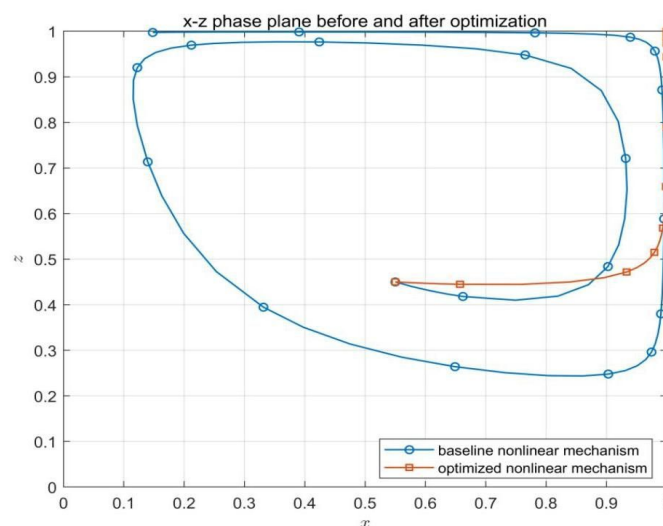


Figure 18. Phase-plane evolution of the tripartite subject x-z under the optimized nonlinear dynamic reward-and-penalty mechanism.

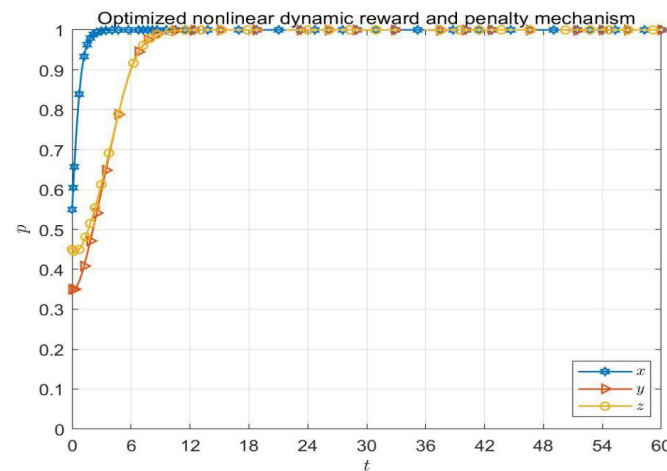


Figure 19. Time evolution of strategies of the tripartite subject under the optimized nonlinear dynamic reward-and-penalty mechanism.

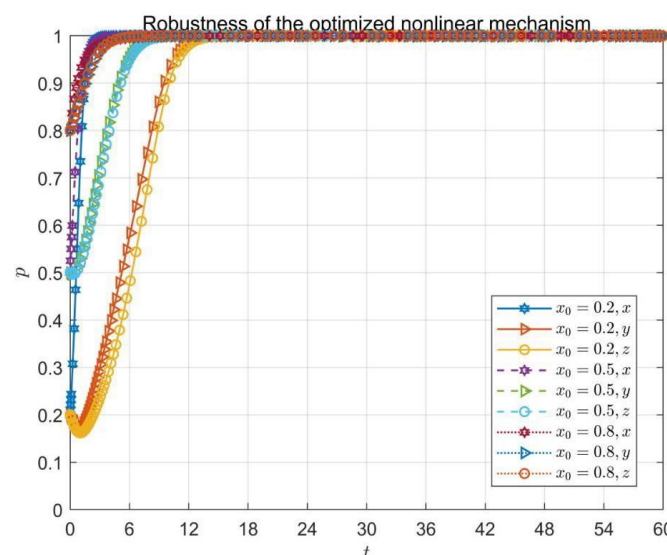


Figure 20. Robustness test of the optimized nonlinear dynamic reward-and-penalty mechanism under different initial probabilities.

5. Discussion

This study constructs a tripartite evolutionary game model of collaborative disaster governance in the Guangdong–Hong Kong–Macao Greater Bay Area (GBA) under a dynamic reward–punishment mechanism and uses numerical simulation to compare the governance effects of different incentive regimes. The simulation results reveal how the design of reward–punishment functions shapes the stability and direction of multi-actor collaboration, and several mechanisms warrant further discussion.

First, the absence of any reward–punishment mechanism makes it difficult to resolve the low level of collaboration between local actors and social actors. Even when the regional coordinating regulatory authorities are willing to actively promote collaboration, the system may remain in an incompletely collaborative state if local and social actors lack sufficient incentives and constraints. This indicates that the regulatory authorities’ leadership willingness alone is not a sufficient condition for system-wide collaboration; without aligned incentives for the other two parties, unilateral promotion cannot overcome free-riding and underinvestment.

Second, a static reward–punishment mechanism can improve the behavior of some actors but struggles to simultaneously balance the regulatory authorities’ fiscal burden, the actors’ sense of fairness, and collaborative stability. Fixed rewards may induce subsidy dependence, while fixed penalties cannot be adjusted precisely according to disaster risk and the degree of passivity. The mechanism’s rigidity therefore generates side effects that may offset its intended benefits, particularly by eroding the regulatory authorities’ willingness to lead under sustained fiscal pressure.

Third, a linear dynamic reward–punishment mechanism has certain optimizing effects, but in the GBA’s cross-institutional and cross-regional governance scenarios it may still produce strategy fluctuations and intermittent instability. This suggests that dynamism alone does not necessarily bring stable collaboration; the decisive factor is whether the reward–punishment functions are aligned with multi-actor collaborative performance and the degree of passive behavior. When the functional form fails to match the heterogeneity and complexity of cross-boundary collaboration, dynamic adjustment can amplify rather than dampen oscillations.

Fourth, an optimized nonlinear dynamic reward–punishment mechanism can drive the system to converge toward an “actively promoting–proactively collaborating–actively participating” state. The underlying policy logic is threefold: rewards should be linked to the complementarity and level of collaboration among local actors, social actors, and the regional coordinating regulatory authorities; penalties should progressively correspond to passive collaboration and negative participation; and higher-level support should reduce the fiscal pressure on the regional coordinating regulatory authorities. The combination of incremental incentives and progressive constraints allows the mechanism to reinforce desirable behavior while containing the costs that undermine the regulatory authorities’ leadership role.

Taken together, these findings show that the governance outcome depends less on whether incentives are present than on whether their functional structure matches the collaborative performance and passivity of a multi-actor system—an insight consistent with a systems perspective on cross-boundary disaster governance.

6. Conclusions

This paper modeled collaborative disaster governance in the GBA as a tripartite evolutionary game among the regional coordinating regulatory authorities, local emergency management actors, and social participation actors, and compared four scenarios through numerical simulation: no mechanism, static mechanism, linear dynamic mechanism, and nonlinear dynamic reward-and-punishment mechanism. The analysis yields four main conclusions: (1) in the absence of a reward–punishment mechanism, the system tends to remain in a low-collaboration state even when the regulatory authorities is willing to lead; (2) a static mechanism improves targeted behaviors but cannot balance fiscal burden, fairness, and stability, and risks subsidy dependence; (3) a linear dynamic mechanism offers partial improvement but may induce strategy fluctuations in cross-institutional, cross-regional settings; and (4) under the tested assumptions and parameter values, a parameter-adjusted nonlinear dynamic mechanism increases the possibility of the system converging toward the desirable “actively promoting–proactively collaborating–actively participating” state.

Based on these conclusions, the following recommendations are proposed: 1) Establish a GBA disaster governance collaborative performance evaluation system, incorporating information sharing, joint drills, resource dispatch, response timeliness, and post-disaster recovery into the basis for rewards and punishments. 2) Establish a differentiated dynamic subsidy mechanism that provides increasing rewards for high-quality collaboration and for contributions at critical nodes. 3) Improve accountability-recovery and

credit-constraint mechanisms, implementing progressive penalties for behaviors such as late or omitted reporting, refusal of mutual aid, and false participation. 4) Strengthen higher-level regulatory authorities' support for the stability of regional coordination platforms to avoid excessive reward expenditures that weaken promotion incentives. 5) Incorporate social organizations, platform enterprises, and infrastructure operators into a normalized emergency collaboration network.

This study has several limitations that point to future research directions. The model relies on simulated rather than empirical parameters, and the three-actor abstraction simplifies the heterogeneity within each group. Future work could calibrate the reward–punishment functions with field data from GBA emergency events, introduce additional actor types or sub-regional heterogeneity, and incorporate stochastic disturbances to test the robustness of the nonlinear mechanism under uncertainty.

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