

ORIGINAL RESEARCH ARTICLE

Water pollution control within an eco-evolutionary game framework with environmental feedback

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Abstract

Water pollution control (WPC) is inherently dynamic, characterized by a feedback loop between strategic behavior and water quality (WQ): polluters' choices alter WQ, while changes in WQ, in turn, influence those choices. This paper employs an eco-evolutionary game (EEG) framework to characterize this relationship and models WPC as a dynamic system in which strategy frequencies and the water environment co-evolve. The model is linear and encompasses two strategies: compliant discharge and non-compliant discharge. The paper derives all equilibrium states, determines their stability conditions, and elucidates how four incentive parameters shape the system's behavior. Four long-term outcomes are possible: bistability, dominance of a single strategy, a stable mixed-strategy equilibrium, and limit-cycle (LC) oscillations. The results indicate that LC oscillations arise when two conditions are met: the dominant incentive parameters are both positive, and the environmental feedback rate falls below a critical threshold. With a baseline payoff matrix, a slow feedback rate ($\epsilon = 0.1$) produces an LC spanning $x \in [0.02, 0.98]$ and $x \in [0.10, 0.60]$, with strategic shifts leading environmental responses. A stable mixed-strategy equilibrium emerges under rapid feedback: raising ϵ to 0.4 yields convergence to $(x, n) \approx (0.55, 0.55)$, and a scan over $\epsilon \in (0.05, 0.5)$ locates the threshold at $\epsilon_{crit} \approx 0.15$, with an abrupt rather than gradual transition. When both leading incentives are negative, the system becomes bistable, latching onto (0, 0) or (1, 1) within about 100 time units. The paper then examines how policy instruments—such as environmental taxes and emissions trading—drive transitions between these dynamic modes by altering the four incentive parameters and the environmental feedback rate. It is argued that the recurring pollute-first, treat-later cycle in water pollution governance is not merely a consequence of policy failure but rather the product of the co-evolutionary process between strategies and the environment.

Keywords: Eco-evolutionary game; Environmental feedback; Water pollution control; Evolutionary dynamics

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1. Introduction

Water pollution control (WPC) is a dynamic process in which strategies and water quality (WQ) conditions mutually influence each other. When enterprises choose to comply with

or violate regulations, they change WQ; conversely, changes in WQ reshape the incentive structures these enterprises face. This two-way feedback indicates that WPC cannot be understood as a linear progression from policy instruments to environmental outcomes; rather, it is a dynamic system in which strategic and environmental changes co-evolve and mutually drive one another.¹⁻⁵ However, existing studies often treat environmental quality as an exogenous function of policy intensity.⁶ Consequently, these studies struggle to explain the recurring pollution–treatment–re-pollution cycle observed in WPC. Research on water pollution governance can be broadly categorized into three streams: technological pathways, policy instruments, and governance structures.

Technologically, advances in wastewater treatment have improved WPC effectiveness. However, conventional biological treatment processes are proving increasingly inadequate for removing emerging contaminants.⁷ For a long time, little attention has been paid to how treatment technologies influence the strategic choices of pollution-discharging entities.⁸

Regarding policy instruments, market-based environmental regulatory tools have attracted sustained attention in WPC. While WQ trading (WQT)⁹ offers theoretical cost advantages, its application in the water pollution sector is far less widespread than air emission trading; the main challenge is the unobservability and stochastic nature of non-point source pollution. An assessment of the River Alde WQT project in the United Kingdom reveals that WQT faces critical challenges—such as price volatility, inadequate credit verification, and the shifting of pollution rather than genuine emission reductions—and that, without robust regulation, the mechanism could allow wealthy polluters to offset rather than reduce their environmental impact.¹⁰

In recent years, evolutionary game theory (EGT) has been widely applied to strategy selection and decision-making in domains such as finance, economics, the environment, public safety, and supply chains.¹¹⁻¹⁸ Notably, it is used to analyze strategic interactions among government, enterprises, and the public in WPC.¹⁹⁻²⁹ For example, Estalaki *et al.*²⁶ proposed a method based on EGT to determine the penalty functions that environmental agencies should impose on polluters. Mahjouri and Ardestani²⁹ adopted a different approach, proposing a game theory-based method for managing inter-basin water transfers that integrates economic, equity, and environmental criteria. In these studies, however, the environmental state is reduced to a static parameter rather than treated as a dynamic variable that co-evolves with strategies; as a result, the bidirectional feedback

mechanism is overlooked.

Theoretically, the eco-evolutionary game (EEG) framework proposed by Tilman *et al.*¹ offers a suitable analytical tool to overcome these limitations. This framework integrates the dynamic evolution of strategy frequencies and the dynamic changes in environmental states into a unified system. The environment is no longer a static backdrop for the game; it becomes an endogenous variable: strategic behaviors alter the environment, and the environment, in turn, shapes the incentive structures that govern those strategies.³⁰

While this framework has been applied to fields such as resource management, public goods provision, and the evolution of cooperation, its application to systematic modeling and policy analysis in WPC remains underexplored. WPC is particularly well suited to an EEG theory perspective for three reasons. First, the aquatic environment exhibits significant cumulative effects and time lags. Second, the compliance decisions of polluting enterprises demonstrate clear strategic complementarity or substitutability. Third, environmental regulations themselves are adjusted in response to the state of the aquatic environment; deteriorating WQ often triggers stricter regulation, whereas improvements may lead to regulatory relaxation. Consequently, a feedback loop³¹ is established between strategies and the environment.

Inspired by the work of Tilman *et al.*¹, this study models water pollution governance as a dynamical system in which strategy frequencies and the state of the water environment are mutually coupled. A detailed comparison of this study with the previous research—covering aspects such as numerical values, methodologies, research gaps, and objectives—is presented in Table 1. Prior eco-evolutionary work¹ established the feedback mechanism but left it uncalibrated for water pollution. Empirical WQT assessments¹⁰ document price volatility and weak credit verification without linking instrument design to dynamic regime transitions. In contrast, the present model is calibrated with an explicit payoff matrix and yields quantitative thresholds: at $\epsilon = 0.1$, a limit-cycle (LC) spanning $x \in [0.02, 0.98]$ and $n \in [0.10, 0.60]$, at $\epsilon = 0.4$, an interior equilibrium $x^* \approx n^* \approx 0.55$ reached after ≈ 150 time units. Then, a critical feedback rate $\epsilon_{crit} \approx 0.15$ with an abrupt rather than gradual transition.

The novelty of this paper lies in four key areas:

- (i) Modeling. It applies an EEG framework to WPC and constructs a linear model that facilitates analytical tractability, identifying the parametric conditions that lead to four distinct dynamic outcomes. Prior EGT studies of WPC environmental quality as an

Table 1. A detailed comparison of this study with the research of previous scholars

Study	Method	Gaps	Objective
Tilman <i>et al.</i> ¹	Environmental dynamics	Environment static	EEG framework
Weitz <i>et al.</i> ²	Strategy–environment feedback	Oscillating commons under-studied	Analyze oscillating commons
Wang <i>et al.</i> ⁶	Differential game	Public participation overlooked	Model pollution with public participation
Estalaki <i>et al.</i> ²⁶	Evolutionary game + penalty design	Penalties not dynamically optimized	Design penalty functions
Mahjouri and Ardestani ²⁹	Game theory + multi-criteria	WQ in inter-basin transfer neglected	Manage inter-basin allocation
Shi <i>et al.</i> ²⁸	Evolutionary game + central punishment	Vertical interaction under-analyzed	Analyze central punishment
Shi <i>et al.</i> ⁸	Evolutionary game + prospect theory	Behavioral factors ignored	Study behavioral economics of supervision
Vangipuram <i>et al.</i> ¹⁰	Empirical WQT assessment	WQT regulation gaps unclear	Evaluate WQT effectiveness
This paper	EEG + simulation	Environment static	Four dynamic regimes; $\epsilon_{crit} \approx 0.15$; interior equilibrium $(x, n) \approx (0.55, 0.55)$; limit cycle $x \in [0.02, 0.98]$, $n \in [0.10, 0.60]$; diagnostic (Δ_H^1, δ_H^0) map

Abbreviations: EEG: Eco-evolutionary game; WQ: Water quality; WQT: Water quality trading.

exogenous function of policy intensity (Wang *et al.*⁶; Estalaki *et al.*²⁶; Shi *et al.*²⁸; Mahjouri and Ardestani²⁹), so the environment is a static backdrop. Tilman *et al.*¹ introduced the feedback mechanism but left it uncalibrated for WPC. This paper, by contrast, endogenizes WQ n as a state variable coupled to the strategy frequency x through $\dot{x}$ and $\dot{n}$, and derives closed-form stability conditions for all equilibria.

- (ii) Numerical. Prior EEG analyses are largely qualitative or use arbitrary parameter values. Here, a payoff matrix calibrated to basin-scale water pollution ($R_1 = 10$, $T_1 = 14$, $S_1 = 8$, $P_1 = 11$; $R_0 = 6$, $T_0 = 3$, $S_0 = 2$, $P_0 = 1$) yields quantitative regime boundaries: $\epsilon_{crit} \approx 0.15$, an interior equilibrium at $(x, n) \approx (0.55, 0.55)$ reached after ≈ 150 time units, and an LC spanning $x \in [0.02, 0.98]$, $n \in [0.10, 0.60]$. No prior water pollution EGT study reports such thresholds.
- (iii) Gaps. Two gaps are closed. First, empirical WQT assessments (Vangipuram *et al.*¹⁰) documented price volatility and weak credit verification but never linked instrument design to dynamic regime transitions. This paper does so analytically. Second, prior EEG work (Weitz *et al.*²) analyzed oscillating commons but did not identify the feedback-rate threshold that separates oscillation from stability. This paper locates it at $\epsilon_{crit} \approx 0.15$ and shows the transition is abrupt,

not gradual.

- (iv) Metrics. The paper translates heterogeneous instruments—environmental taxes, emissions trading, and monitoring capacity—into adjustments of four incentive parameters $(\Delta_L^1, \Delta_H^1, \delta_L^0, \delta_H^0)$ and the feedback rate ϵ , and plots them on a diagnostic (Δ_H^1, δ_H^0) map. This converts the abstract call for a policy mix into a concrete rule: exit Zone B by making $\Delta_L^1 < 0$ or $\delta_H^0 < 0$; lock in low emissions by entering Zone A or C; or raise ϵ above ϵ_{crit} . Prior studies offer no such metric-level mapping.

2. Methodology

2.1. Eco-evolutionary game framework and modeling of water pollution control

2.1.1. General framework

The EEG framework proposed by Tilman *et al.*¹ comprises two coupled dynamic equations. Let x_i denote the frequency of strategy i in the population, and n represent the normalized environmental state, where $n = 0$ represents the worst WQ and $n = 1$ represents the best WQ. The strategy dynamics are described by the replicator³⁰ in **Equation 1**:

$$\dot{x}_i = x_i (\pi_i(x, n) - \bar{\pi}(x, n)) \quad (1)$$

here, π_i is the fitness of an individual adopting strategy i ,

and $\bar{\phi} = \sum_j x_j \pi_j$ is the average fitness of the population.^{32,33} The environmental dynamics are given by **Equation 2**:

$$\dot{n} = \epsilon_1 f(n) - \epsilon_2 h(x, n) \quad (2)$$

where $f(n)$ is the intrinsic environmental dynamics without policy intervention, $h(x, n)$ is the influence of the policy set on the environment, and ϵ_1 and ϵ_2 respectively characterize the ratio of the rate of change of the intrinsic environment and the rate of change of the policy-driven environment to the rate of policy evolution.

For the two-strategy scenario, let strategy L be the low-impact strategy (compliant emissions) and strategy H be the high-impact strategy (non-compliant emissions). The ecological evolutionary system can be expressed as **Equations 3 and 4**:

$$\dot{x} = x(1-x)(\pi_L(x, n) - \pi_H(x, n)) \quad (3)$$

$$\dot{n} = \epsilon \alpha (x - n) \quad (4)$$

Equation 4 corresponds to the depleting-resource specification¹, in which the strategy frequency x establishes a target environmental level, and the environment approaches this target at a rate of $\epsilon \alpha$. This formulation is applicable to water pollution problems involving the accumulation of pollutants.

2.1.2. The linear eco-evolutionary game model for water pollution control

The flowchart of the EEG model for WPC is shown in **Figure 1**.

Consider a population of polluting enterprises within a watershed, where each enterprise can choose between compliant discharge (Strategy L , frequency x) and non-compliant discharge (Strategy H , frequency $1-x$). Water environmental quality is represented by a normalized index $n \in [0, 1]$. $n=1$ corresponds to excellent WQ (low pollution load), while $n=0$ corresponds to degraded WQ (high pollution load).

(a) Revenue structure

Assume that a firm's payoff depends on its own strategy, the composition of strategies within the population, and the WQ state n , and that a linear payoff structure is adopted as in **Equation 5**:

$$\Pi(n) = (1-n) \begin{bmatrix} R_0 & S_0 \\ T_0 & P_0 \end{bmatrix} + n \begin{bmatrix} R_1 & S_1 \\ T_1 & P_1 \end{bmatrix} \quad (5)$$

where the subscripts 0 and 1 correspond to the poor-quality environment state ($n=0$, poor WQ) and the rich-quality environment state ($n=1$, good WQ), respectively. The parameter interpretations of the payoff matrix are shown in **Table 2**.

At this point, the fitness values of strategy L and strategy H are given by **Equations 6 and 7**, respectively:

$$\pi_L(x, n) = (1-n)(R_0x + S_0(1-x)) + n(R_1x + S_1(1-x)) \quad (6)$$

$$\pi_H(x, n) = (1-n)(T_0x + P_0(1-x)) + n(T_1x + P_1(1-x)) \quad (7)$$

(b) Environmental dynamics

In WPC, the intrinsic environmental dynamics correspond to the natural purification capacity of the water body. If a decay-type model is adopted, the environmental dynamics are represented by **Equation 4**. The intuitive meaning of **Equation 4** is that the WQ state n tends toward the target WQ level x —determined by the current strategy composition—with the rate of approach governed by the environmental feedback speed $\epsilon \alpha$. This formulation corresponds exactly to the resource decay model proposed by Tilman *et al.*¹

2.2. Equilibrium and stability analysis

2.2.1. Four incentive parameters

The dynamic behavior of linear EEG can be fully characterized by four parameters with intuitive interpretations in terms of behavioral incentives. In the context of WPC, these four parameters are defined by **Equations 8–11**:

$$\Delta_L^1 = \pi_H(1, 1) - \pi_L(1, 1) = T_1 - R_1 \quad (8)$$

$$\Delta_H^1 = \pi_H(0, 1) - \pi_L(0, 1) = P_1 - S_1 \quad (9)$$

$$\delta_L^0 = \pi_L(1, 0) - \pi_H(1, 0) = R_0 - T_0 \quad (10)$$

$$\delta_H^0 = \pi_L(0, 0) - \pi_H(0, 0) = S_0 - P_0 \quad (11)$$

Their technical interpretations are:

- (i) Δ_L^1 : the payoff advantage of a single firm switching to non-compliance when $n=1$ and all other firms comply. It refers to the profit advantage a single enterprise gains by switching to non-compliant discharge when WQ is excellent ($n=1$) and all other enterprises are in compliance. If $\Delta_L^1 > 0$, there exists an arbitrage opportunity for the “first violator”: regulatory oversight is relatively lax and environmental capacity is abundant, meaning the short-term profits from non-compliance are sufficient to offset the associated risks.
- (ii) Δ_H^1 : the payoff advantage of maintaining non-compliance when $n=1$ and all other firms violate. When WQ is high, and all other enterprises are in violation, this analyzes the relative payoff advantage for a single enterprise to maintain a non-compliant strategy versus switching to compliance. If $\Delta_H^1 > 0$, it indicates that all enterprises are pursuing non-compliant discharge practices.
- (iii) δ_L^0 : the payoff advantage of remaining compliant

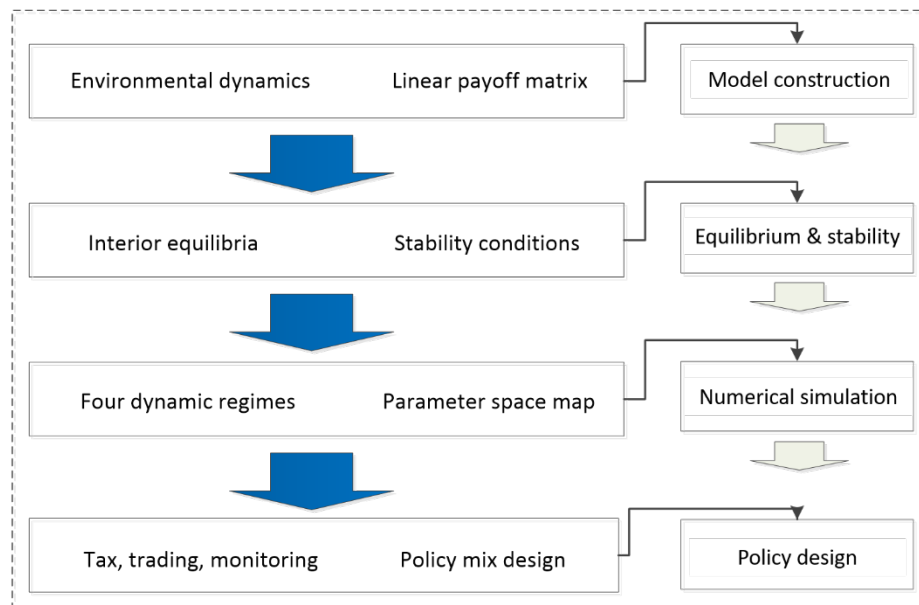


Figure 1. The flowchart of the eco-evolutionary game model for water pollution control

Table 2. The parameter interpretations of the payoff matrix

Parameters	Location	Meaning
R_0	(L, L $n = 0$)	Corporate profits when WQ is poor and both parties meet discharge standards
S_0	(L, H $n = 0$)	Corporate earnings when WQ is poor, with the firm meeting standards while others are in violation
T_0	(H, L $n = 0$)	Enterprise revenue when WQ is poor, the enterprise is in violation, and others are compliant
P_0	(H, H $n = 0$)	Corporate profits when WQ is poor and both parties are in violation
R_1, S_1, T_1, P_1	$n = 1$	Corresponding returns when WQ is good

Abbreviation: WQ: Water quality.

when $n = 0$ and all other firms comply. The relative benefit advantage for a single firm to remain compliant rather than switching to non-compliance when WQ deteriorates ($n = 0$) and all other firms are already compliant. If $\delta_L^0 > 0$, it implies that “compliance pays off” under environmental pressure.

- (iv) δ_H^0 : the payoff advantage of being the first to comply when $n = 0$ and all other firms violate. This refers to the competitive advantage gained by a single enterprise that takes the lead in achieving compliance when WQ is deteriorating, and other enterprises are in violation. If $\delta_H^0 > 0$, it signifies the existence of a first-mover advantage for the enterprise that is the first

to implement pollution control measures.

2.2.2. Equilibrium analysis

The equilibria of Equations 3 and 4 satisfy $\dot{x} = 0$ and $\dot{n} = 0$. Let $\dot{n} = 0$, then, $x = n$. Then, let $\dot{x} = 0$, then, $x(1-x)(\pi_L(x, n) - \pi_H(x, n)) = 0$. By solving this equation, the following equilibrium solution can be obtained.

- (a) Boundary equilibrium

When $x = 0$, $n = 0$, and the boundary equilibrium is (0, 0). When $x = 1$, $n = 1$, and the boundary equilibrium is (1, 1).

- (b) Internal balance

Let $x = n$, then $\pi_L(x, x) - \pi_H(x, x) = 0$. Evaluating **Equations 6** and **7** at $x = n$ yields a quadratic **Equation 12** in x :

$$\alpha_2 x^2 + \alpha_1 x + \alpha_0 = 0 \quad (12)$$

where:

$$\begin{cases} \alpha_2 = (R_1 - S_1 - T_1 + P_1) - (R_0 - S_0 - T_0 + P_0) \\ \alpha_1 = (S_1 - P_1) - (S_0 - P_0) - (R_1 - S_1 - T_1 + P_1) + (R_0 - S_0 - T_0 + P_0) \\ \alpha_0 = S_0 - P_0 \end{cases}$$

The solution corresponds to at most two interior equilibria. Let the interior equilibria be denoted by (x_+, n_+) and (x_-, n_-) , where x_+ is always a saddle point (unstable), while x_- may be either stable or unstable.

2.2.3. Stability conditions

(a) Stability of boundary equilibrium

The necessary and sufficient condition for the equilibrium $(0, 0)$ to be stable is shown in **Equation 13**:

$$\delta_H^0 < 0 \quad (13)$$

In other words, when WQ is poor and all other enterprises violate regulations, no single enterprise has an incentive to be the first to switch to compliance. Economically, this condition implies that once a whole river basin is locked into a race to pollute, no individual enterprise has an incentive to be the first to curb its pollution.

The necessary and sufficient condition for the stability of the equilibrium $(1, 1)$ is shown in **Equation 14**:

$$\delta_L^0 < 0 \quad (14)$$

In other words, when WQ is good, and all other enterprises comply, no enterprise has an incentive to be the first to violate the rules.

(c) Stability and oscillation conditions for internal equilibrium

The condition for the internal equilibrium (x_-, n_-) to be unstable is:

$$\Delta_H^1 + \delta_L^0 > 0 \quad (15)$$

$$\Delta_H^1 \delta_L^0 > \Delta_L^1 \delta_H^0 \quad (16)$$

$$\epsilon < \epsilon_{crit} \quad (17)$$

Here, ϵ_{crit} can be expressed analytically in terms of the system parameters. **Equation 17** represents a key feature of EEG: the emergence of oscillations requires the rate of environmental feedback to be slower than the rate of strategy evolution. In the context of WPC, this implies that the processes of WQ recovery or deterioration must be sufficiently slow; only when changing strategies occurs

more rapidly than changing the environment can the time lag between strategy and environment generate periodic overshooting and oscillation.

2.2.4. Dynamic partitioning

Based on the aforementioned conditions, the EEG of WPC can be divided into four dynamically distinct zones:

- (i) Zone A: Bistability: $(\Delta_L^1 < 0, \delta_H^0 < 0)$. The system ultimately converges to $(0, 0)$ or $(1, 1)$, depending on initial conditions.
- (ii) Zone B: Oscillation/Mixing equilibrium: $(\Delta_L^1 > 0, \delta_H^0 > 0)$. The system exhibits LC oscillations.
- (iii) Zone C: Dominance of low-impact strategies and bistability: $(\Delta_L^1 < 0, \delta_H^0 > 0)$. Under these circumstances, enterprises have reason to spearhead the environmental movement, whereas high emissions yield no benefits. A low-emission equilibrium is sustainable, while a high-emission equilibrium is not.
- (iv) Zone D: Dominance of high-impact strategies and bistability: $(\Delta_L^1 > 0, \delta_H^0 < 0)$. Here, firms can profit by being the first to pollute, and there is no reward for leading an environmental movement. The high-emission equilibrium is the one that survives; the low-emission equilibrium does not.

3. Results and discussion

3.1. Numerical simulation and scenario analysis of water pollution control

3.1.1. Baseline scenario setting

To operationalize the theoretical analysis, a set of parameters reflecting the typical characteristics of WPC in river basins was established:

- (i) Payoff matrix for high WQ ($n=1$): $R_1=10$, $T_1=14$, $S_1=8$, $P_1=11$.
- (ii) Payoff matrix for WQ deterioration ($n=0$): $R_0=6$, $T_0=3$, $S_0=2$, $P_0=1$.

Thus, $\delta_L^0 = R_0 - T_0 = 3 > 0$ (there is an incentive to follow the environmental movement), $\delta_H^0 = S_0 - P_0 = 1 > 0$ (there is an incentive to lead the environmental movement). All four parameters were positive, placing the system in Zone B (oscillatory/mixed equilibrium zone). Environmental dynamic parameters: $\epsilon = 0.1$ (slow environmental feedback speed, consistent with the time-lag characteristics of water pollution accumulation and recovery), and $\alpha = 1$.

3.1.2. Scenario 1: Limit-cycle oscillation under slow environmental feedback ($\epsilon = 0.1$)

This scenario was selected to test the first prediction of the theoretical analysis: that when $\Delta_L^1 > 0$ and $\delta_H^0 > 0$ and the environmental feedback rate falls below ϵ_{crit} , the

system should exhibit an LC rather than converge to any equilibrium. Here, let $\epsilon = 0.1$, initial state $(x_0, n_0) = (0.3, 0.5)$, and integration time $t = 300$. The simulation results for LC oscillations under slow environmental feedback are shown in Figure 2.

The two sets of simulated images clearly illustrate the system's LC behavior. Figure 2A shows that, starting from the initial point (0.3, 0.5), the trajectory rapidly expands outward and eventually converges to a closed LC. This LC exhibits a distinct, asymmetric peanut shape: the trajectory makes sharp turns at the ends where x approaches 0 and 1, while remaining relatively smooth in the intermediate x region. The environmental nullcline $n = x$ (gray dashed line) passes through the interior of the LC, indicating that the system operates alternately on either side of this line. The LC spans an x -range of approximately [0.02, 0.98] and an n -range of approximately [0.10, 0.60]. Figure 2B shows that the compliance frequency $x(t)$ and the water environmental quality $n(t)$ exhibit clear periodic oscillations with a phase difference: the peak of $x(t)$ (approx. 0.98) occurs slightly before the peak of $n(t)$ (approx. 0.60), indicating that strategic shifts precede environmental responses. The oscillation amplitude of $x(t)$ is substantial (ranging from 0.02 to 0.98), implying that the corporate population periodically switches between states of near-universal compliance and near-universal non-compliance. Conversely, the oscillation amplitude of $n(t)$ is relatively moderate (ranging from 0.10 to 0.60), reflecting the water body's buffering capacity and lag in response to emission changes.

This scenario reflects the classic policy cycle phenomenon in WPC: once compliance rates are high and WQ has improved, short-term incentives for non-compliance re-emerge ($\Delta_L^1 = 4 > 0$), leading some

enterprises to violate regulations first. As non-compliance spreads, WQ gradually deteriorates until environmental pressure becomes severe enough to trigger a new round of pollution control measures ($\delta_H^0 = 1 > 0$), causing compliance rates to rise again. The system fails to stabilize at any single equilibrium, instead becoming trapped in a cycle of control–rebound–renewed control–renewed rebound.

3.1.3. Scenario 2: Stable mixed-strategy equilibrium with rapid environmental feedback ($\epsilon = 0.4$)

Scenario 2 was deliberately constructed as the controlled counterpart of Scenario 1: the payoff matrix and initial condition were held identical, and only ϵ was raised from 0.1 to 0.4. Here, $\epsilon = 0.4$, initial state $(x_0, n_0) = (0.3, 0.5)$, and integration time $t = 300$. The simulation results of stable mixed-strategy equilibrium with rapid environmental feedback are shown in Figure 3.

Figure 3A shows that, starting from (0.3, 0.5), the trajectory does not expand outward to form a LC. Instead, it spirals inward to converge to an interior equilibrium point. This equilibrium lies on the line $n = x$, with coordinates approximately (0.55, 0.55). The spiral convergence is clearly visible: initially, the trajectory circles the phase plane several times with gradually decaying amplitude before finally stabilizing at the equilibrium point. Figure 3B shows that both $x(t)$ and $n(t)$ approach their steady-state values through damped oscillations: $x(t)$ rises gradually from 0.3 to approximately 0.55, while $n(t)$ adjusts synchronously from 0.5 to approximately 0.55. After about 150 time units, both curves stabilize, and periodic fluctuations cease.

The above results indicate that when environmental feedback is sufficiently rapid, the time lag between policy strategies and WQ outcomes is compressed, thereby eliminating the dynamic basis for oscillation. The system

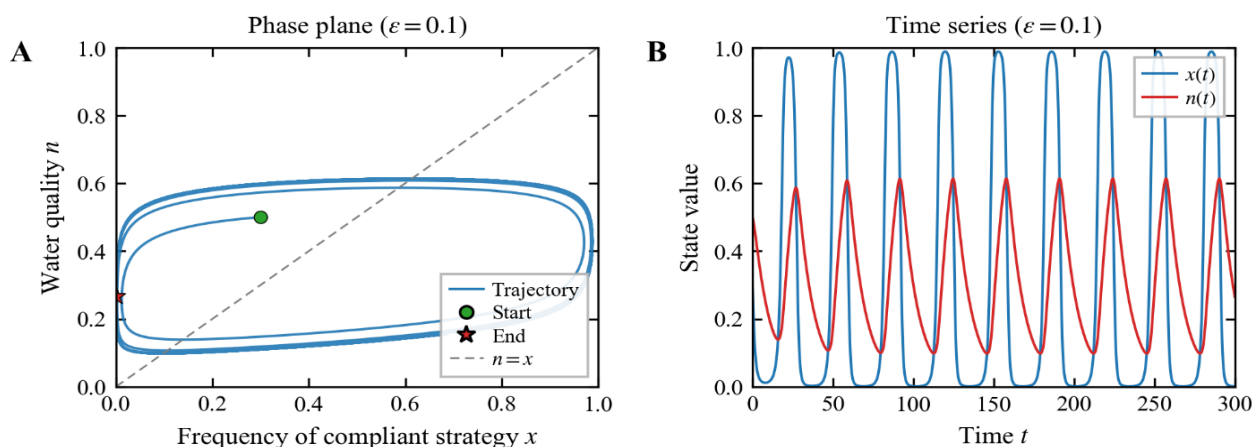


Figure 2. The simulation results of limit-cycle oscillations under slow environmental feedback. (A) Phase plane trajectory. (B) Time series.

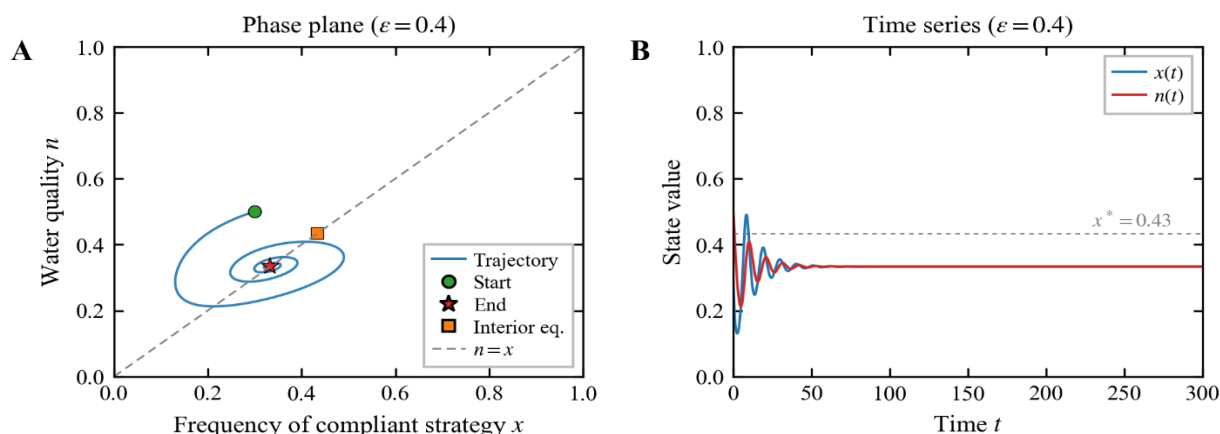


Figure 3. The simulation results of stable mixed-strategy equilibrium with rapid environmental feedback. (A) Phase plane trajectory. (B) Time series.

stabilizes at a mixed equilibrium characterized by partial compliance and partial violation, where approximately 55% of enterprises choose to comply with discharge standards, maintaining WQ at a moderate level. This finding suggests that enhancing the real-time nature of environmental monitoring and enforcement responses (increasing ϵ) can, in itself, suppress policy cycles without requiring changes to the enterprises' profit structures.

3.1.4. Scenario 3: Bistable latching (Zone A)

Zone A was chosen precisely because it captures the most policy-relevant form of bistability. Since both first-mover incentives are negative, the system offers neither a first-polluter advantage nor a first-mover advantage in environmental protection, and its eventual state hinges entirely on initial conditions. Here, payoff parameters were adjusted to enter Zone A. Specifically, the payoff for non-compliance was reduced when WQ is good (reducing T_1 from 14 to 8 and P_1 from 11 to 9) such that $\Delta_L^1 = -2 < 0$. Simultaneously, the payoff for non-compliance by both parties was increased when WQ deteriorates (increasing P_0 from 1 to 3) such that $\delta_H^0 = -1 < 0$. The environmental feedback rate was set to $\epsilon = -2$. The system starting from two different initial conditions was solved: initial Condition 1 (biased towards high emissions), $(x_0, n_0) = (0.4, 0.3)$ and initial Condition 2 (biased towards low emissions), $(x_0, n_0) = (0.6, 0.7)$. The simulation results of bistable latching (Zone A) are shown in Figure 4.

Figure 4A shows two trajectories converging to two distinct boundary equilibria. The red trajectory, starting at (0.4, 0.3), eventually converges to (0, 0)—a state where all firms discharge non-compliant emissions and WQ deteriorates—while the blue trajectory, starting at (0.6, 0.7), eventually converges to (1, 1)—a state where all firms meet emission standards, and WQ is excellent. These two

trajectories are separated in the phase plane by a separatrix that extends roughly along the direction of $n = x$. The two stable equilibria, (0, 0) and (1, 1), are marked with a square and a triangle, respectively. Figure 4B shows the red curve $x(t)$ gradually declining from 0.4 to 0 and the blue curve $x(t)$ gradually rising from 0.6 to 1, both stabilize at their respective equilibria after approximately 100 time units.

This scenario illustrates the path dependence and lock-in effects inherent in WPC. When the incentives driving both pollution-related gains and environmental protection efforts are negative, the system exhibits bistability. A river basin may become trapped in a high-emission, deteriorating-WQ state owing to lax regulation in its early stages, whereas another may settle into a virtuous low-emission, high-WQ state thanks to strict early-stage regulation. Once such lock-in takes hold, mere policy fine-tuning is unlikely to reverse it; escaping it requires an external shock strong enough to cross the threshold.

3.1.5. Scenario 4: Environment feedback rate scanning and threshold analysis

Scenarios 1 and 2 establish the existence of an oscillation-stability transition at two discrete values of ϵ . Scenario 4 generalizes this comparison into a systematic scan, the purpose of which is to locate ϵ_{crit} numerically and to verify that the transition is sharp rather than gradual, as implied by Equation 17. Here, keeping the baseline gain matrix fixed, the system scans values of ϵ in the range [0.05, 0.5], covering a total of 40 points. For each ϵ , the system was integrated from the initial state (0.3, 0.5) up to $t = 500$, the amplitudes of $x(t)$ and $n(t)$ were then calculated over the latter half of this time interval to determine whether the system is in an oscillatory state. The simulation results of environment feedback rate scanning and threshold analysis are shown in Figure 5.

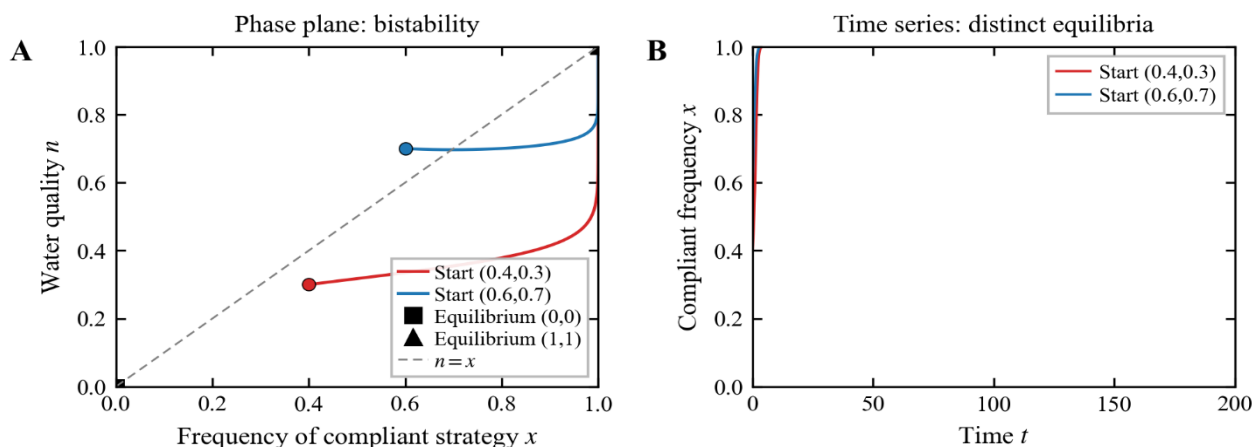


Figure 4. The simulation results of bistable latching (Zone A). (A) Phase plane: bistability. (B) Time series: distinct equilibria.

Figure 5A shows that when ϵ is small ($\epsilon < 0.15$), the terminal states x and n fluctuate over a wide range, indicating that the system is in a LC. The terminal values stop changing much once ϵ rises above roughly 0.15. They settle around an interior equilibrium near 0.55. Figure 5B illustrates this transition more clearly: the amplitudes of x and n are significantly greater than zero when $\epsilon < \epsilon_{crit}$, drop sharply to near-zero levels around $\epsilon \approx 0.15$, and subsequently remain stable. Using an amplitude threshold of 0.01 as the criterion, the critical value is estimated to be $\epsilon_{crit} \approx 0.15$.

These results point to a critical threshold in the speed of environmental feedback: below it, the system oscillates, whereas above it, the system gravitates toward stability. This threshold implies a key leverage point for policy intervention: the feedback speed need not be increased indefinitely, as oscillations can be effectively suppressed once the critical value ϵ_{crit} is exceeded.

3.1.6. Comprehensive partitioning map: Parameter space of four types of dynamical behavior

Here, a 40×40 grid scan was performed on the parameter plane (Δ_H^1, δ_H^0) . For each parameter set, the system was integrated starting from two different initial conditions: (0.3, 0.3) and (0.7, 0.7), and the dynamic behavior was classified based on the final-state amplitude and the difference between final states into: stable equilibrium/single-strategy dominance (green), LC oscillation (yellow), and bistability (blue). The simulation results of the comprehensive partitioning map: parameter space of four types of dynamical behavior are shown in Figure 6.

The comprehensive zoning diagram clearly illustrates the distribution of the three types of dynamic behaviors across the parameter plane. The blue region (bistability)

occupies the lower-left section of the diagram, corresponding to parameter combinations where $\delta_H^0 < 0$ and Δ_H^1 is small, representing a scenario lacking incentives to lead the environmental protection movement and also lacking sufficient incentives to follow the pollution discharge dividend. The green region (stable equilibrium/single-strategy dominance) covers the right half and upper section of the diagram, corresponding to a large area where $\Delta_H^1 > 0$ and $\Delta_H^0 > 0$. The yellow region (LC oscillation) appears in the upper-right corner—a specific sub-region where both $\Delta_H^1 > 0$ and $\delta_H^0 > 0$ are satisfied—though its area is relatively limited. Notably, the boundaries of the yellow region are not determined solely by the conditions $\Delta_H^1 > 0$ and $\delta_H^0 > 0$, they also depend on the additional conditions specified in Equations 16 and 17.

The results above indicate that the integrated zoning map provides policymakers with a parameter map. The effects of policy instruments can be understood as shifting the system's position on the map: environmental taxes and strict penalties primarily reduce Δ_H^1 (shifting the system to the left), helping it exit the bistable zone. Ecological compensation and green credit primarily increase δ_H^0 (shifting the system upward), helping it enter the stable zone. Meanwhile, increasing the environmental feedback speed (raising ϵ) can push the system from the yellow oscillatory zone into the green stable zone without altering its parameter coordinates.

By comparing the simulation results of the four scenarios with the theoretical analysis, the following inferences can be drawn:

- (i) Oscillation represents a genuine dynamic risk in WPC. The LC observed in Scenario 1 indicates that the system can fall into periodic fluctuations even when all enterprises are rational and possess

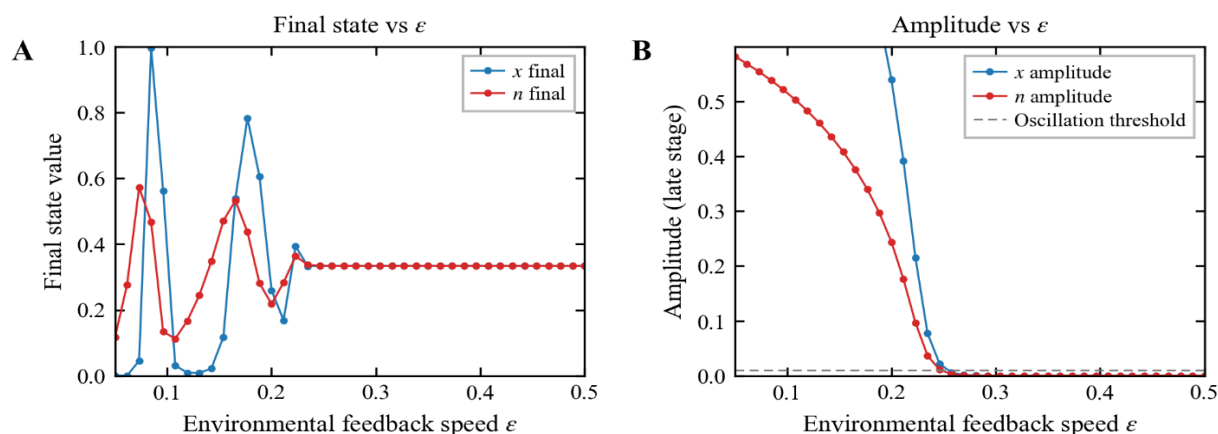


Figure 5. The simulation results of environment feedback rate scanning and threshold analysis. (A) Final state vs. ϵ . (B) Amplitude vs. ϵ .

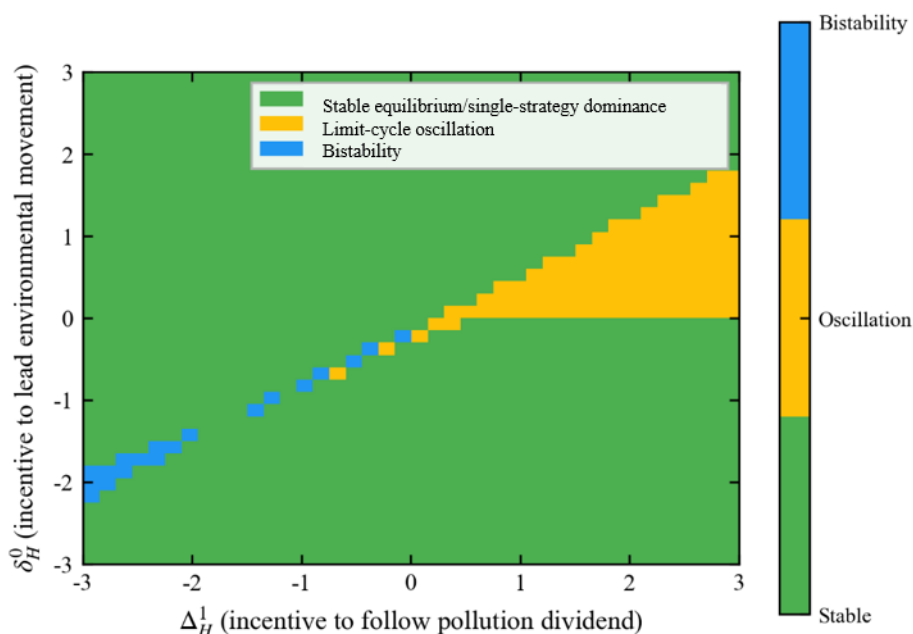


Figure 6. The simulation results of the comprehensive partitioning map: Parameter space of four types of dynamical behavior

perfect information. Such oscillations arise when the incentives for both the leading-in-pollution strategy (driven by associated gains) and the leading-in-environmental-protection strategy are simultaneously positive ($\Delta_L^1 > 0$ and $\Delta_H^0 > 0$), and the speed of environmental feedback falls below a critical threshold ($\epsilon < \epsilon_{crit}$). This condition likely holds true in many river basin WPC contexts, where a common pattern involves the relaxation of regulatory oversight following WQ improvements, subsequently leading to a resurgence in violations.

(ii) The speed of environmental feedback is a critical yet

often overlooked policy variable. Scenarios 2 and 4 demonstrate that increasing ϵ can shift the system from oscillation to stability without altering the payoff structure. In terms of policy implementation, ϵ corresponds to the real-time nature of WQ monitoring, the timeliness of enforcement responses, and the transparency of information disclosure. This implies that investing in environmental monitoring and enforcement capacity-building exerts an independent stabilizing effect, rather than merely serving to passively detect violations.

(iii) Bistable lock-in presents a more formidable

governance challenge. Scenario 3 demonstrates that when the incentives driving both types of changes are negative, the system may become trapped in a high-emissions/deteriorating WQ state. This lock-in is characterized by path dependency and is difficult to reverse through mere policy fine-tuning. Breaking the lock-in requires a sufficiently strong external shock—such as drastically increasing penalties for violations (thereby changing the sign of Δ_L^1), establishing a robust ecological compensation mechanism (increasing Δ_H^0), or triggering political attention through a major environmental incident.

- (iv) Policy instruments should be used in combination to “move” the system within the parameter space. A composite zoning map reveals that a single instrument typically affects only one parameter dimension: environmental taxes primarily influence Δ_H^1 , ecological compensation mainly affects δ_H^0 , and the development of monitoring capacity impacts ϵ . Effective governance strategies require selecting an appropriate mix of instruments based on the system’s current position on the zoning map to steer it toward the stable equilibrium zone.

3.2. Mechanism for adjusting incentive parameters of policy instruments

The numerical simulations in Section 3.1 reveal a troubling conclusion: WPC systems do not necessarily converge to the ideal state of low emissions and high WQ. The LC observed in Scenario 1 indicates that, even when all enterprises are rational and fully informed, the system can still become trapped in a cyclical pattern of treatment–rebound–retreatment. Meanwhile, the bistability found in Scenario 3 suggests that a river basin can become locked into a high-emissions and degraded WQ trap due to initial conditions—such as regulatory history, industrial structure, and environmental awareness—a situation that is difficult to reverse through mere policy fine-tuning. These findings naturally raise a question: given that the system’s long-term outcome depends on four incentive parameters ($\Delta_L^1, \Delta_H^1, \delta_L^0, \delta_H^0$) and the environmental feedback speed (ϵ)—specifically their positions within the dynamic zones—can policy instruments “shift” the system by altering these parameters?

This section aims to address the questions raised above. The policy value of the EEG framework lies in its ability to translate disparate policy instruments into adjustments of the four incentive parameters and the rate of environmental feedback, thereby providing policy design with clear dynamic objectives.

3.2.1. Environmental taxes and pollution charges

Environmental taxes³⁴ influence incentive parameters by altering the cost differential between non-compliance and compliance strategies. Let τ represent the tax rate per unit of pollutant discharge; the payoff for the non-compliance strategy decreases by τ , whereas the payoff for the compliance strategy remains unchanged. Consequently, $\Delta_L^1 = T_1 - R_1$ decreases as τ increases. When τ exceeds a critical threshold, Δ_L^1 shifts from positive to negative, causing the system to exit Zone B and eliminating the leading incentive for oscillation. Conversely, $\delta_H^0 = S_0 - P_0$ increases with τ , thereby strengthening the incentive to spearhead environmental protection efforts. In essence, the environmental tax serves to price non-compliance when WQ is high.

3.2.2. Pollution permit trading

Emissions trading affects strategy payoffs through allowance quotas and trading prices.³⁵ Let P_e denote the allowance price; compliant firms generate revenue of $P_e \cdot \Delta q$ by selling surplus allowances, while non-compliant firms incur a cost of $P_e \cdot \Delta q$ to purchase them. This mechanism influences the payoffs of both strategy types across the two environmental states: When $n=1$, the price of emissions allowances is typically low, resulting in limited inhibition of Δ_L^1 . When $n=0$, allowances tighten, and prices rise, significantly reinforcing δ_H^0 . Consequently, the impact of emissions trading is state-dependent: it is more effective at reinforcing incentives for pollution control when the environment is deteriorating, but not necessarily effective at curbing incentives to pollute when environmental conditions are favorable.

3.2.3. Dynamic objectives of the policy mix

From the perspective of EEG theory, an ideal policy mix should aim to achieve the following dynamic objectives:

- (i) Suppressing oscillation (exiting Zone B). Oscillation entails the highest policy costs, signifying cyclical waste in pollution-control investment and persistent public skepticism about the effectiveness of governance. The condition for exiting Zone B is achieving $\Delta_L^1 < 0$ or $\delta_H^0 < 0$. Environmental taxes or strict penalties are the most direct tools for suppressing Δ_L^1 .
- (ii) Lock in the low-emission equilibrium (entering Zone A or C). In Zone A, the high-emission equilibrium can be rendered unstable by making δ_H^0 negative. In Zone C, the stability of the low-emission equilibrium can be ensured by maintaining $\delta_H^0 > 0$ while setting $\Delta_L^1 < 0$.

- (iii) Accelerate environmental feedback (increase ϵ). Even while remaining within Partition B, increasing ϵ can shift the system from a LC to a stable mixed equilibrium. Online monitoring, rapid enforcement, and real-time public oversight all help shorten the time it takes for WQ to respond to discharges.

The framework extends static-environment evolutionary game studies by endogenizing WQ and by mapping policy instruments onto four incentive parameters and the feedback rate ϵ . This reveals state-dependent instrument effectiveness and identifies feedback speed as an independent stabilizing lever. However, the analysis assumes a well-mixed watershed, a representative firm, binary strategies, and linear payoffs, and the parameters are illustrative rather than empirically calibrated. These limitations suggest directions for future work, including spatial heterogeneity, multi-strategy games, nonlinear ecological dynamics, and empirical estimation of the feedback rate.

4. Conclusion

Drawing on the EEG framework, this paper develops a dynamic model of the bidirectional feedback between strategies and the environment in WPC. The main conclusions are as follows:

- (i) The speed of environmental feedback is a crucial yet often overlooked policy variable. Raising ϵ from 0.1 to 0.4 with an unchanged payoff matrix drives the system to an interior equilibrium at $(x, n) \approx (0.55, 0.55)$, with damped oscillations dying out after about 150 time units. A scan over $\epsilon \in [0.05, 0.5]$ locates the threshold at $\epsilon_{crit} \approx 0.15$, and the transition is abrupt rather than gradual: below it amplitudes remain substantial, above it they collapse to near zero. Feedback speed thus need not be increased indefinitely, and it operates as an independent stabilizing lever rather than a passive detection device.
- (ii) Bistable lock-in is a more formidable challenge. In the Zone A scenario ($\Delta_L^1 = -2, \delta_H^0 = -1$), trajectories from (0.4, 0.3) and (0.6, 0.7) converge to (0, 0) and (1, 1) respectively within roughly 100 time units, separated by a separatrix running roughly along $n = x$. Such lock-in is path-dependent and cannot be reversed by policy fine-tuning alone; it requires a sufficiently strong external shock.
- (iii) A combination of policy instruments should be employed to steer the system's state within the parameter space. Environmental taxes primarily serve to weaken incentives for polluting first, while eco-compensation strengthens incentives for prioritizing

environmental protection first. Monitoring capacity, meanwhile, influences the rate of environmental feedback. Relying on a single policy instrument is often ineffective. Successful governance instead requires an appropriate mix of instruments tailored to the system's current state, so as to steer it toward a stable, low-emission equilibrium. Phase diagrams offer a diagnostic tool here: policymakers can identify the basin's current dynamic evolutionary state and then select the corresponding instruments to steer the system into the stable region.

The innovation of this study lies in providing a unified dynamic explanation for the recurring pollute-first, clean up-later policy cycle. This cyclical phenomenon stems not merely from regulatory failure or corporate shortsightedness but may instead be an endogenous outcome of the co-evolution of strategies and the environment under specific incentive structures. Existing studies largely rely on traditional evolutionary game models based on static environments, failing to explain why this cyclical pattern persists even when rational behavior prevails. By incorporating a bidirectional feedback mechanism between strategy frequency and WQ, this study reframes the core policy challenge: the aim is not to eliminate non-compliance altogether but to steer the system away from a state of fluctuation. The practical value of this framework lies in enabling policymakers to diagnose the dynamic evolutionary state of a river basin and to select policy mixes that guide the system toward a stable, low-emission state.

This analysis is subject to several limitations. First, it relies on a linear payoff structure and simplified environmental dynamics, without accounting for spatial heterogeneity, firm size distribution, interactions among multiple pollutants, or the complexity of the institutional environment. Second, the model restricts the strategy space to a binary choice (compliance versus non-compliance), omitting intermediate strategies such as partial compliance or technological upgrades. Future research could extend this framework to incorporate multi-strategy evolutionary games in an ecological context.

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Conflict of interest

The authors declare they have no competing interests.

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Availability of data

The data used in the paper are simulated data, which are already included in the article.

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