Individual Decision-Making in Coupled Agent-Environment Systems

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Abstract. Understanding how individual decisions shape environmental outcomes is critical as climate targets grow more ambitious. Traditional mean-field and two-strategy frameworks overlook individual-level cognition, dynamic risk perception, and evolving social norms. We develop a spatially explicit agent-based model (ABM) in which heterogeneous agents choose between climate-friendly and degradative actions via adaptive utility functions integrating environmental preference, social pressure, and ecosystem feedback, augmented with sub-models for dynamic risk-perception, shifting-baseline effects, and memory-based spillovers. Complemented by a mean-field approximation, phase plots and clustering analysis reveal critical tipping points, multi-stability, oscillatory behavior, and scale-free cluster formation across rationality and adaptation-speed regimes — dynamics absent from the mean-field model. These results identify the cognitive and social thresholds that determine whether socio-ecological systems collapse or recover, offering a basis for designing targeted, climate-positive interventions.

Keywords: Agent-based modeling · Coupled human–environment systems · Climate decision-making · Dynamic risk perception

1 Introduction

In recent years, global climate policy has coalesced around ambitious greenhouse-gas (GHG) reduction targets such as the European Union's *Fit for 55* legislative package which mandates a 55% reduction in net GHG emissions by 2030 relative to 1990 levels, aiming for climate neutrality by 2050 [8]. As other major emitters adopt similar goals, understanding how collective human behaviour shapes and responds to environmental change becomes increasingly critical. Agent-Based Models (ABMs) provide a means to explore these coupled socio-ecological dynamics by linking individual decision-making to emergent environmental outcomes.

Kraan et al. (2019) [13] developed ACT, an ABM that departs from mean-field assumptions, to study how heterogeneity, leadership, and local network structures drive

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critical transitions in low-carbon energy systems. However, ACT does not explicitly incorporate dynamic environmental feedback on individual risk perception or evolving social norms. Tilman et al. (2020) [31] introduced an eco-evolutionary game framework capturing bidirectional feedback between strategic behaviour and environmental state, yet its mean-field abstraction overlooks cognitive mechanisms such as shifting baselines, pluralistic ignorance, and memory-based spillovers, as well as the heterogeneity of real social networks. Calls for integrating formal decision-making theories into ecological ABMs further underscore the need for psychologically grounded models [9, 12, 27].

Accordingly, this study integrates behavioural theory with coupled human–environment modeling to examine how dynamic cognition, social influence, and environmental feedback jointly shape collective outcomes. Specifically, we investigate:

1. *How do the steady-state equilibria differ in the coupled socio-ecological model?*
2. *What role do social-influence structures play in emergent cooperation?*
3. *What dynamical regimes appear in the ABM but are absent (or smoothed out) in its mean-field approximation?*

Section 2 surveys foundational studies on social norms, coupled human–environment systems, and agent-based climate behaviour. Section 3 introduces the model and its mean-field analysis. The results of our experiments are presented in 4, followed by the discussion in 5 and concluding remarks in 6.

2 Related work

Individual and collective environmental behavior remain difficult to predict. Research across disciplines has identified numerous determinants, with the Theory of Planned Behaviour (TPB) [3, 23] providing a foundational framework linking attitudes, social norms, and perceived behavioural control to behavioural intention.

Existing research identifies multiple drivers of environmental behavior. Cognitive and social mechanisms collectively underscore the need for models capable of capturing evolving perceptions, feedbacks, and heterogeneity in decision rules. Among other mechanisms, risk perception plays a crucial role: individuals act more sustainably when degradation is visible and perceived as reversible [11, 20], but engagement declines when the environment appears either too healthy or too damaged [2, 19, 35]. This nonlinear relationship is compounded by the *shifting-baseline effect* which is the gradual normalization of environmental decline [17, 22, 30]. Additionally, historical inaction can reinforce unfavorable norms, producing *pluralistic ignorance*, a mismatch between private concern and perceived social consensus [7, 14, 16].

Research on *Coupled Human–Environment Systems* (CHES) examines bidirectional feedback between human activity and environmental change [4, 15, 34]. Building on Weitz et al. (2016) [36], Tilman et al. (2020) [31] proposed an evolutionary game-theoretic framework to study dynamic resource dilemmas, later extended to explore agent heterogeneity and tipping points [11,32]. These studies reveal oscillatory dynamics and critical thresholds but rely on representative-agent assumptions, leaving open how micro-level cognition and social influence shape emergent system behavior.

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Agent-based approaches have since emerged to address these limitations, incorporating heterogeneity, social learning, and environmental feedbacks [6, 21, 24]. ABMs have explored opinion dynamics [28, 29], delayed feedback [37], and the evolution of social norms [1, 18, 33]. Others investigate critical transitions and cooperation collapse in environmental contexts [13, 25, 26].

Building on these insights, our model operationalizes and extends TPB within a coupled human–environment framework, embedding cognitive dynamics such as risk perception, pluralistic ignorance, and memory-based spillovers. Although TPB was originally formulated as a static model of intention formation, its structured decomposition of decision factors makes it particularly well-suited for formalization within agent-based models, allowing behavioural components to evolve dynamically as agents respond to social and environmental feedback. By introducing heterogeneity in social influence, cognition, and network topology, we aim to capture emergent patterns such as clustering, oscillatory cooperation, and ecological tipping between collapse and recovery.

3 Theory

We developed an agent-based model for human decision-making in a dynamic environment, in which individuals' behavioural choices are both *informed by* the environment and *affect* the environment. The model explores how individual decisions to adopt pro-environmental behaviors are shaped by environmental feedback and social norms, where agents are arranged on a 2D grid and repeatedly choose between positive and negative environmental actions. In this section, we outline fundamental model mechanics and summarize key analytical results from our corresponding mean-field analysis. We also list the parameter ranges used in our implementation in Table 1.

3.1 Environmentally-influenced decision-making

Consider a population of $k \in \mathbb{N}$ individuals, $N = \{1, \ldots, k\}$, who repeatedly choose between adopting *Climate-friendly* (`C`) or *Degradative* (`D`) behaviors. Individuals are located at the 30×30 2D lattice with Moore neighborhoods.

An individual i's decisions depend on their own perceptions of both the environment (n_i^t) and the social norms imposed by their neighborhood of influence ($\overline{a}_i^t$).

Perception of the environment $n_i^t \in [0, 1]$ represents agent i's perceived local environmental state, where 0 denotes fully degraded, and 1 denotes ideal conditions. It can amplify an individual's preference for climate-friendly behaviour when the environment is viewed as *damaged but reversible*, but also dampen it when the environment is particularly healthy [11, 20].

Social norms ($\overline{a}_i^t$) provide stability in decision-making via the status quo, with potential to both slow and sustain climate-friendly behaviour [5,7,10,20,23]. To compute α_i^t we use a memory size m parameter, which is an implementation parameter controlling the time horizon used to compute α_i^t. Larger m creates greater inertia and delayed feedback; smaller m produces more reactive dynamics. [1]

[1] We henceforth omit the t superscript for visual clarity, except where doing so would cause ambiguity.

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Symbol	Parameter	Simulation Specification	Mean-Field Specification
Mapped Parameters			
N, k	Pop. Size	30×30 spatial grid	Total individuals k
λ	Agent Rationality	Logit stochasticity $[0, 6]$	tanh argument scaling
w, b_2	Peer Pressure	Agent attribute $w_i \in [0, 1]$	Expected value $\mathbb{E}[w_i]$
s, γ_s	Support Update Rate	Dynamic support and rate	Aggregate state; $dP/dt = 0$
m	Memory Length	Time horizon for norms	Assumed stationary.
Simulation-Only Parameters			
`env_up_fn`	Env. update function	Exponential env. decay	N/A (standard ODE)
`prediction`	Neighbor behavior prediction	Linear neighbor behavior regression	N/A (assumes independence)
r, `moore`	Topology	Moore radius grid connectivity	N/A (assumes well-mixed)
`env_adap`	Environmental Change Calc.	Linear vs adaptive change logic	N/A
T, `repeats`	Run Stats	1000 steps; 5000–50000 repeats	N/A (analytical fixed point)

Table 1: Mapping of theoretical symbols and simulation-specific implementation parameters.

We model an agent i's decisions using a discrete-choice logit model, with homogeneous rationality parameter λ and representative utility V_i in Equation 1.

$$\begin{aligned} V_i(C) &= (1 - w_i) \cdot s_i - w_i \cdot (1 - \overline{a_i})^2 \\ V_i(D) &= (1 - w_i) \cdot (4 - s_i) - w_i \cdot (1 + \overline{a_i})^2 \end{aligned} \tag{1}$$

where $s_i \in [0, 4]$ is i's level of preference for climate-friendly behaviour and $w_i \in [0, 1]$ is a static attribute which moderates the relative contributions of individual preference and social pressures to i's decisions. The probability that i chooses an action $a \in \{D, C\}$ is given by:

$$\mathbb{P}(a_i^t = a) = \frac{\exp(\lambda V_i(a))}{\exp(\lambda V_i(C)) + \exp(\lambda V_i(D))} \tag{2}$$

The rationality λ is defined as the sensitivity of an agent's action choice to utility differences in the logit-based decision rule in Equation 2. Larger values of λ correspond to more deterministic, utility-maximizing behavior, while smaller values introduce greater stochasticity in decision making.

3.2 Coupled human-environment dynamics

Agents' action preferences and local environment states vary with respect to one another according to the dynamical system in Equations 3 and 4 respectively. The former governs

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how perceived environmental state reshapes preferences, while the latter governs how aggregated behavior reshapes the environment. The function σ is the logistic function, $\sigma : n \mapsto 4n(1-n)$. It is a static, nonlinear transformation that imposes an inverted-U relationship between the perceived environmental state and the motivational impact on preference. It reflects the empirical idea that motivation is highest when the environment is moderately degraded ($n \approx 0.5$), and lower when conditions are either pristine ($n \to 1$) or completely collapsed ($n \to 0$).

The relative rates at which the environment is restored/degraded, and preference for cooperation/defection increase are set by parameters β_n^+, β_n^- and β_s^+, β_s^-, with the overall environment and preference update speeds defined by γ_n and γ_s.

$$\frac{1}{\gamma_s}\frac{ds_i}{dt} = \beta_s^+ \cdot \sigma(n_i^t)(4 - s_i^t) - \beta_s^- \cdot (1 - \sigma(n_i^t))s_i^t \tag{3}$$

$$\frac{1}{\gamma_n}\frac{dn_i}{dt} = \beta_n^+ \cdot (1 - n_i^t)\alpha_i^t - \beta_n^- \cdot n_i^t(1 - \alpha_i^t) \tag{4}$$

In the model (Eq. 4), α_i^t is a rescaled version of the action variable $a_i^t \in \{-1, +1\}$, used to express behavior on the unit interval so that it can be interpreted as an intensity or proportion. Specifically, it is defined as $\alpha_i^t = \frac{a_i^t+1}{2}$, which maps $a_i^t = -1$ (degradative action) to $\alpha_i^t = 0$ and $a_i^t = +1$ (climate-friendly action) to $\alpha_i^t = 1$. This allows α_i^t to enter Eq. 4 as a continuous measure of the contribution of agent behavior to environmental change.

All experiments in this report (with the exception of the sensitivity analysis) take $\beta_n^+ = \beta_n^- = \beta_s^+ = \beta_s^- = 1$

3.3 Mean-field analysis

We derive the equations for the expected mean action (Eq. 6) and its temporal dynamics (Eq. 7) via a mean-field analysis, making the following simplifying assumptions:

1. $w_i = \mathbb{E}[w_i] := w$ for each agent $i \in N$,
2. $\frac{dP}{dt} = 0$ for each $i \in N$, such that $s_i^t = s$, and
3. $\mathbb{P}(a_i, a_j) = \mathbb{P}(a_i) \cdot \mathbb{P}(a_j)$ for each pair of agents $i, j \in N$.

Expanding sub-terms in Equation 2 yields a simplified expression for an agent's expected action:

$$\mathbb{E}[a_i] = \tanh(\lambda[(1 - w_i)(s_i - 2) + 2w_i\overline{a_i}]) \tag{5}$$

We extend Equation 5 to derive a fixed-point expression for the population-level expected action, $a_{pop} := \mathbb{E}[a]$,

$$a_{pop} = \tanh(\lambda\overbrace{[(1 - w)(s - 2) + 2wa_{pop}]}^{z}) \tag{6}$$

which has between 1 and 3 solutions, at most two of which are stable. The three-solution case corresponds to pluralistic ignorance, where the influence of social norms is sufficient to sustain a behavioural state different from the mean agent preference. For

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this to occur, it is necessary (though not sufficient) that $\frac{1}{2\lambda w} < 1$ — that is, the expected social pressure or rationality must be sufficiently large. We obtain the dynamics of a_{pop} as the time derivative of Equation 6:

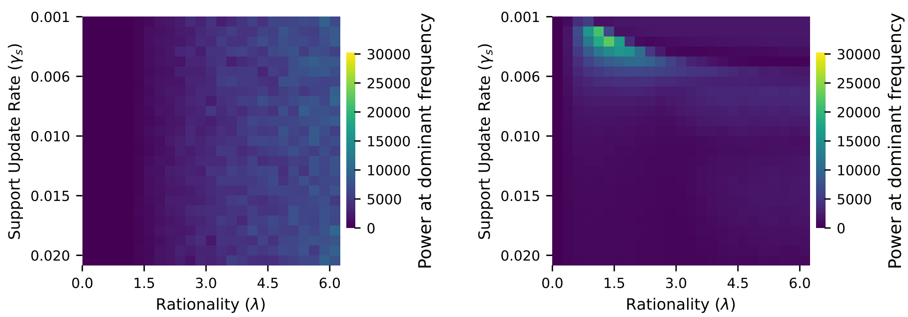
$$\frac{da_{pop}}{dt} = \frac{(1-w)\lambda\,\mathrm{sech}^2(\lambda z^t)}{1-2\lambda w\,\mathrm{sech}^2(\lambda z^t)} \cdot \frac{ds}{dt} \tag{7}$$

4 Results

4.1 Dynamic Preferences Unlock Complexity

Parameter sweeps over rationality (λ) and the rate of change of action preference (γ_s) reveal the system's primary behavioral regimes with different model characteristics. Sensitivity analysis (Appendix C in the Supporting Information) indicates that these parameters are primary drivers of system behavior, motivating the focus on these parameters in the phase and criticality analysis.

System models with both uniform and random social pressure coefficients $b_2 \in [0.0, 1.0]$ which don't use dynamic preferences (where internal support s remains static) or neighborhood prediction (where social pressure is a simple average of current neighbor actions) expresses noisy periodic environmental status that increases in power over λ. These noisy oscillation result in uniform average of 0.5 environmental status at the final timestep $t = 1000$.



(a) Linear neighborhood prediction (no dynamic action preferences) expresses global influence of λ on oscillation power

(b) Dynamic action preferences (no neighborhood prediction) express boundary transition dynamics with stabilized oscillation behavior

Fig. 1: Phase-space characterization of dominant Fourier power indicates the strength of oscillatory dynamics. Both use random social pressure coefficients $b_2 \in [0.0, 1.0]$.

Allowing agents to linearly predict their neighborhood's future actions using a rolling linear regression with 10-step memory (m) to forecast neighbor behavior introduces some behavioral "momentum" that generally increases variance of oscillation power as λ increases (Fig. 1a), but still lacks any dynamic system behavior.

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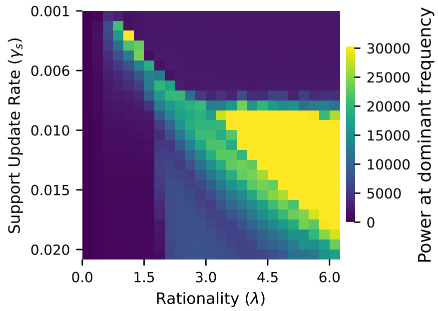
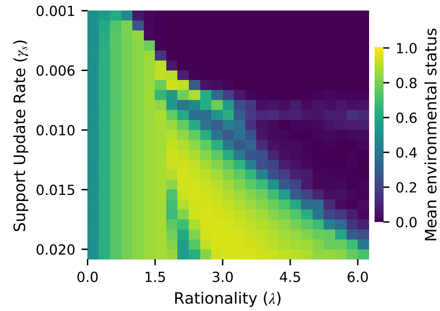
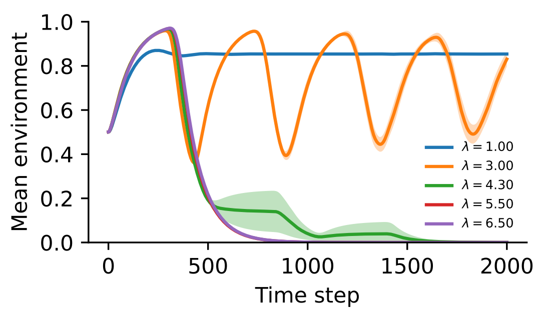


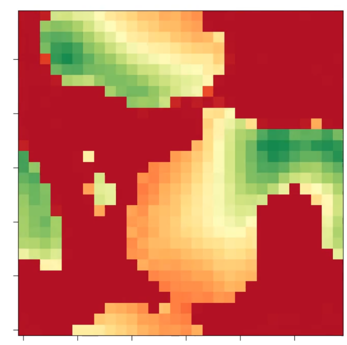
(a) Dominant Fourier power of the environmental time series, capturing the strength of oscillatory dynamics.



(b) Mean environmental status representing the long-term system state. A transition between low- and high-environment regimes is visible across the parameter space.



(c) Representative environment status time series at $\gamma_s = 0.015$ showing stable oscillations, high-variance dynamics, and collapse across λ over 2000 time steps.



(d) Clusters of stable environment state form with $\gamma_s = 0.01$ and $\lambda = 6.0$ at time step $t = 1000$[2]

Fig. 2: Parameter sweep over agent rationality λ and support update rate γ_s, under dynamic action preferences, no neighborhood prediction, a single-radius neighborhood, and uniform 1.0 social pressure.

The introduction of dynamic preferences without neighborhood prediction allows agents to adapt their tendency to cooperate through a feedback loop: they increase support for climate-friendly action when the environment is damaged but reversible, yet become complacent when it is healthy. This new system dynamic begins to reveal complexity in Fig. 1b where oscillations lose their noise and begin to express regular behavior over their parameter sets, giving us a distinct transitionary boundary of high oscillation power that separates the system into a low γ_s, low environmental status attractor, and a high γ_s, high environmental status attractor.

These two regimes get expanded into three when we change our random social pressure coefficients to instead be uniform $b_2 = 1.0$, creating a new dynamic system

[2] Color indicates environmental state $\in [0, 1]$, from fully degraded (red, 0) to healthy (green, 1)

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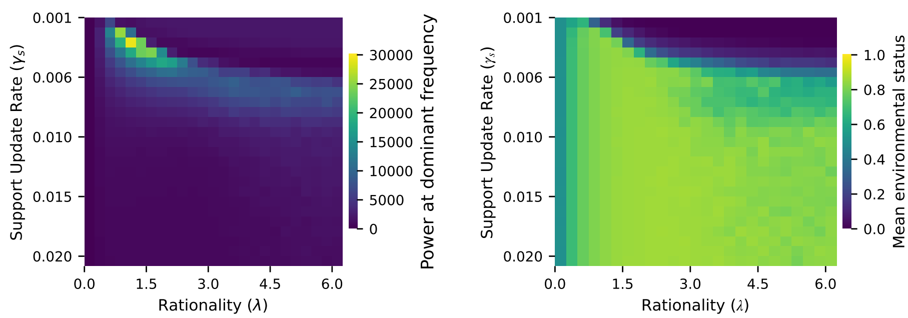
with distinct regions (Fig. 2a): A diagonal spike in oscillation strength, a “square" of oscillation activity in the range greater than $\gamma_s \approx 0.08$ and $\lambda \approx 2.0$ and a distinct separation of low and high oscillation within the “square", divided by the diagonal.

Time-series slices at $\gamma_s = 0.01$ (Fig. 2c) confirm that the dark region corresponds to stable oscillations, the diagonal to high-variance oscillations, and the bright region to transient spikes followed by collapse. Systems that don’t collapse to a single environmental status see unique emergent behavior such as those seen at $t = 1000$ in Fig. 2d.

The difference between Fig. 1b and Fig. 2a is likely caused by the encoded momentum of a uniformly extreme b_2 social pressure coefficient reinforcing the oscillation power already present in the system with dynamic action preferences. By returning to random social pressure coefficients $b_2 \in [0.0, 1.0]$ and now combining both dynamic preferences and neighborhood prediction, we can better represent a world where individual agents are influenced by their neighbors non-uniformly, and where they are able to make locally informed decisions based on neighbors’ and environment.



(a) Dominant Fourier power, indicating the strength of oscillatory dynamics.

(b) Mean environmental status at $t = 1000$ expresses distinct regimes of system state

Fig. 3: Phase-space characterization of system dynamics under dynamic action preferences, linear neighborhood prediction, and random social pressure $b_2 \in [0.0, 1.0]$.

The coupled dynamic preferences and neighborhood prediction (Fig. 3) aligns closely with the dynamics observed in Fig. 1b, but distinctly shows how the addition of the neighborhood prediction emphasizes the oscillation power that already exists in the system (Fig. 3a) and introduces the noise (Fig. 3b) that we saw without the dynamic preferences in Fig. 1a. These results show us that neighborhood prediction has a global influence on environmental status "momentum", while the introduction of dynamic preferences creates distinct regimes defined by a boundary of oscillations.

Additionally, if we then parameter sweep across the memory m used for the neighborhood prediction rolling linear regression, we can select specific γ_s values around the boundary observed in Figures 1b and 3. By selecting $\gamma_s = 0.004$ and $\gamma_s = 0.01$ at and around the boundary, we observe additional evidence of tipping behavior where three

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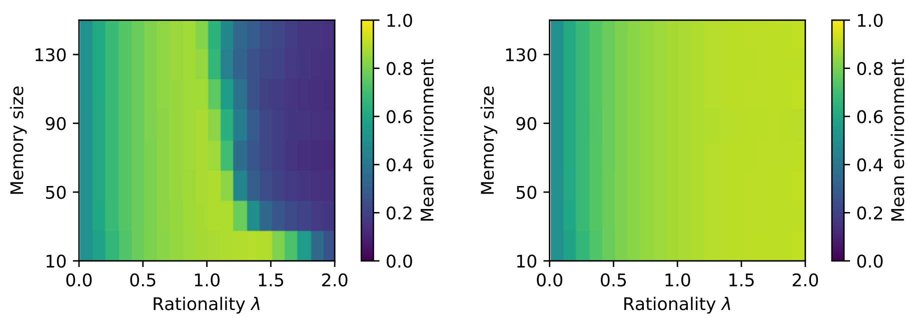
regimes appear (Fig. 4): at low values of λ (order of 10^{-3}) the environment remains nearly neutral ($n^* \approx 0.5$), at high values of λ (order of 10^{-}) but short memory size m, the environmental collapses ($n^* < 0.2$) and finally at high λ but larger memory size m, the environment rapidly recovers ($n^* > 0.8$).

The boundary between collapse and recovery forms a downward-sloping curve in the (m, λ) plane, indicating a possible tipping-point sensitivity, while increasing γ_s to 0.01 largely eliminates collapse, with agents preferentially stabilizing the environment across parameter values.



(a) Equilibrium environment at $\gamma_s = 0.004$ showing a critical boundary where low memory and rationality lead to system collapse.

(b) Equilibrium environment at $\gamma_s = 0.01$. Faster adaptation drives system robustness, maintaining healthy states.

Fig. 4: Phase diagrams of equilibrium environment state at $t = 1000$ across rationality λ and memory mem, under dynamic preferences, linear neighborhood prediction, and random $b_2 \in [0, 1]$.

4.2 Emergent Behavior at Critical Phase Transition

The distinct boundary that we observe in Figures 1b, 3a, 3b, and 4a express a clear phase boundary with possible non-uniform equilibrium environmental states. Since our previous results have shown that dynamic support preference defines the oscillation boundary, we isolate this dynamic by excluding the neighborhood prediction regression, using the same experimental setup from Fig. 1b, allowing us to localize the boundary transition by identifying the steepest gradient in the environment status slice shown in Fig. 5b, and then examining the overall environmental status at $t = 1000$ in Figure 5b.

The environmental status slice in Fig. 5a identifies a sharp transition in system behavior, with the steepest gradient occurring near $\gamma_s = 0.0049$ for $\lambda = 4.0$. We focus on this parameter regime to examine the underlying spatial and statistical structure of the system.

The qualitative snapshot at $t = 1000$ (Fig. 5b reveals a heterogeneous configuration consisting of both isolated cells and clusters with stable environmental states. Unlike

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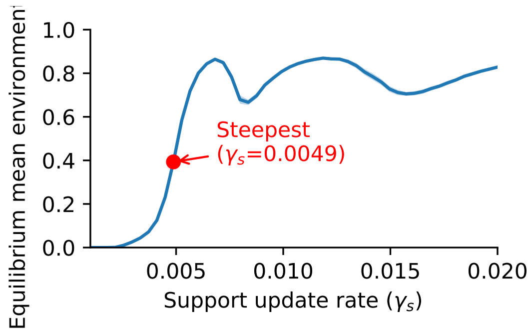
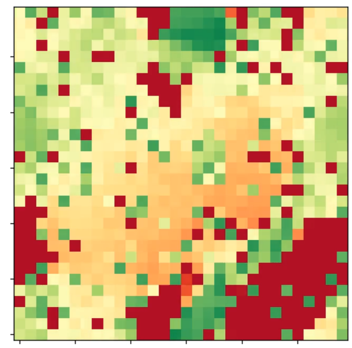
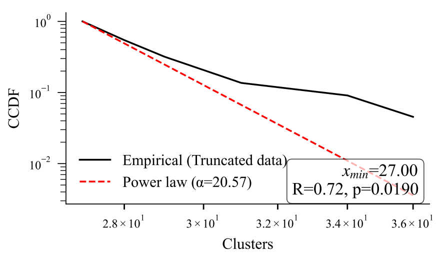


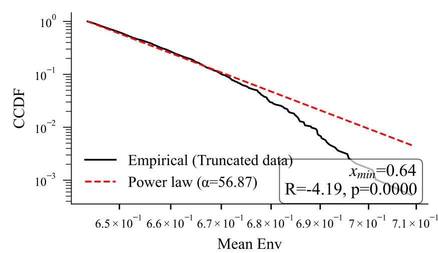
(a) Environmental status slice at γ_s and $\lambda = 4.0$ expresses critical transition boundary using the steepest point.



(b) Qualitative clustering at $\gamma_s = 0.0049$ and $\lambda = 4.0^2$



(c) CCDF of number of clusters in log-log scale ($\gamma_s = 0.0049$, $\lambda = 4.0$) exhibits positive R with statistically significant $p = 0.019$ power law fit tail.



(d) CCDF of environmental status (log-log scale, $\gamma_s = 0.0049$, $\lambda = 4.0$) exhibits negative R with statistically significant $p = 0.0$ rejecting a power law fit tail.

Fig. 5: Phase transition in the model where all agents have dynamic action preference, no neighborhood prediction, and random social pressure weights.

regimes away from the transition boundary where the system converges to uniformly degraded or healthy states, this region exhibits persistent spatial variability, with patches of intermediate and high environmental status coexisting alongside a background dynamic of constantly shifting state. These structures appear semi-stable over time, suggesting a slowing of dynamics near the transition.

To quantify this behavior, we examine the distribution of cluster counts and environmental states across repeated simulations, where the complementary cumulative distribution function (CCDF) of the number of clusters (Fig. 5c) displays a broad, heavy-tailed form with a possible power-law fit tail, indicating substantial variability in the number of coexisting regions. However, while a power-law fit can be applied over a restricted range ($x \geq x_{min}$), the deviation from linearity across the full distribution suggests that the scaling is only approximate. A similar pattern is observed in the distribution of environmental states (Fig. 5d), where the CCDF again exhibits a heavy-tailed shape but instead rejects any clear power law over multiple decades. Together, these

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results indicate that the system near the transition does not exhibit strict scale-free behavior, but instead shows broadened distributions and increased variability consistent with near-critical dynamics.

Overall, the combination of spatial heterogeneity, semi-stable local structure, and broadened distributions supports the interpretation that the system operates in a transition regime characterized by competing local interactions and slowed relaxation dynamics, rather than a fully developed critical state.

4.3 Comparison with the mean-field model

The mean-field model predicts convergence to a single stable equilibrium for a given parameter configuration (λ, γ_s), implying that the system should evolve toward a spatially homogeneous environmental state. This assumption follows from the well-mixed nature of the mean-field approximation, where agents interact only through global averages and local fluctuations are neglected.

In contrast, the agent-based simulations reveal substantial deviations from this behavior, particularly near the phase transition identified in Figures 1b and 3. Rather than converging to a uniform equilibrium, the system exhibits persistent spatial heterogeneity, characterized by coexisting regions of high and low environmental status. As shown in Fig. 5b, these regions remain stable over extended time periods, indicating the presence of locally sustained equilibria.

This discrepancy highlights a key limitation of the mean-field approximation: it cannot capture the emergence of spatial structure driven by local interactions. In the agent-based model, agents respond to *locally experienced* social norms, which vary across space and evolve dynamically, where these localized feedback loops allow subsets of the system to stabilize independently, leading to the formation of semi-stable regions with distinct environmental conditions. Such behavior is fundamentally incompatible with the assumptions underlying the mean-field model.

Sensitivity analysis (Appendix C in the Supporting Information) further supports this interpretation, showing that equilibrium environmental state depends not only on λ, but also on adaptation rates and system size. This dependence implies path-dependent dynamics, in contrast to the unique equilibrium predicted by the mean-field model.

Overall, the mean-field approximation fails to capture the emergence of spatial heterogeneity and locally stable structures, highlighting the importance of explicitly modeling local interactions in coupled agent–environment systems.

5 Discussion

5.1 Policy Implications and Interpretation

While the model is not calibrated to empirical data and therefore does not support direct quantitative prediction, it does provide mechanistic insight into how cognitive, social, and environmental feedbacks may shape collective outcomes. Rather than prescribing specific policies, the results identify classes of mechanisms that influence system behavior within the model. These interpretations are grounded in the mechanism-level results

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from Section 4, where dynamic preferences generate regime transitions, memory and adaptation rates are associated with differences in stability, and local social influence amplifies these dynamics near transition regions.

Across both the mean-field and agent-based formulations, the results suggest that changes in individual perception and social influence can be associated with large differences in environmental outcomes. This indicates that intervention strategies may need to consider not only top-down regulation, but also local decision-making processes and feedback structures.

In particular, the model assumes that behavior responds to environmental state through the support-update dynamics, suggesting that environmental perception may matter for collective outcomes. This is consistent with the possibility that clearer or more persistent environmental feedback could influence behavior, although such interventions were not explicitly modeled here. Memory also emerges as an influential mechanism in the parameter sweeps, suggesting that persistence in communication or institutional continuity may be relevant for sustaining cooperative dynamics, though threshold-specific effects were not directly tested.

The results more directly support the importance of social influence and neighborhood interactions, which play a central role in shaping system dynamics across the reported experiments. More generally, the parameter sweeps reveal sharp transition regions in which nearby parameter values produce very different system states, consistent with tipping-like behavior. Taken together, these findings position the model as a tool for identifying mechanisms and transition regimes that may be relevant for policy design, rather than for evaluating or forecasting the effects of specific policies. Future work incorporating empirical calibration and targeted intervention experiments will be necessary to assess the quantitative relevance of these mechanisms in real-world settings.

5.2 Limitations and Future Work

While the model incorporates behaviorally grounded mechanisms such as adaptive risk perception, social influence, and environmental feedback, several limitations remain. First, social interactions are represented on a fixed Moore neighborhood and therefore do not capture dynamic social ties, heterogeneous influence hierarchies, or evolving communication structures. Second, the model is not calibrated to empirical data, so its current contribution is better understood as mechanism discovery and qualitative insight rather than direct quantitative prediction. Future work should link model components to observed social, environmental, and economic data to assess external validity and improve realism. Third, although the mean-field model provides a useful theoretical benchmark, its relationship to the agent-based simulations remains primarily qualitative. A more formal comparison would clarify where mean-field assumptions break down and how spatial correlations, clustering, and local interactions modify equilibrium behavior. Future work could also extend the model to adaptive network topologies, heterogeneous communication structures, and multi-layer influence processes. Empirical calibration and validation, together with more explicit comparisons between mean-field and agent-based dynamics, would help bridge theoretical insight and applied relevance, and support a more grounded understanding of environmental decision-making in coupled socio-ecological systems.

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6 Conclusion

This model attempts to bridge a research gap [13,31] observed in the study of feedback between environmental status and agent actions, with the aim of better representing how diverse individual decision rules, social influences, and dynamic risk perceptions jointly determine collective environmental outcomes. The model operationalizes the Theory of Planned Behaviour by integrating environmental preferences, social pressure, and perceived action feasibility through dynamic risk perception, predictive neighborhood influence, and agent heterogeneity. Phase-space analysis reveals rich system dynamics: the base model exhibits noisy periodic behavior, while adding a linear neighborhood predictor dampens these oscillations. Dynamic action preferences introduce parameter-dependent oscillations and distinct regime transitions, including shifts between stable and unstable oscillations and between zero and non-zero equilibria. The model also shows evidence of tipping-point behavior, with neutral equilibrium, environmental collapse, and rapid recovery emerging once rationality and memory exceed critical thresholds. Near these transition points, small parameter changes produce large system-wide effects, and simulations display possible scale-free clustering.

While the model is not calibrated for direct prediction, it provides a structured framework for understanding how cognitive, social, and environmental feedbacks interact to produce nonlinear system responses, and thus identifies where and how policy interventions may most effectively influence collective outcomes. Each component represents behavioral mechanisms observed in real-world decision-making. Where individuals become complacent with a good environment and pessimistic in a bad one. Where friends and family influence the desire to act to the detriment or benefit of ourselves. But even in the chaos created by these interacting systems, organized patterns such as equilibria, oscillations, and clustering emerges.

Supporting Information. The supporting information (appendices) can be found at Peterson, V., Sinha, S., Chłopicka, K., Zwart, H., & Roy, D. (2026). Supporting Information: Individual Decision-Making in Coupled Agent-Environment Systems. Zenodo. https://doi.org/10.5281/zenodo.18720295.

Data and Code Availability. The code for the model described in this study can be found at https://github.com/VictorianHues/AgentBasedModeling.

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