The Role of Information in Modulating Cooperation Under the Risk of Ecological Collapse

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Abstract.
Averting critical climate tipping points depends on the coordinated efforts of geopolitical entities, such as countries, major corporations, and cities. However, this cooperation is hindered not only by short-sighted incentives but also made more challenging by uncertainty, both about others' behavior and the actual state of the climate. Despite a growing body of research on international environmental agreements and cooperation under collective risk, the role of information in shaping outcomes remains poorly understood. In this work, we implement a game-theoretic framework to systematically evaluate how access to social and ecological cues shapes long-term cooperation under environmental uncertainty. Preliminary findings suggest that ecological feedback plays a crucial role in sustaining cooperation, whereas social transparency appears less effective than previously thought. This work advances theory by clarifying the role of different forms of reciprocity that operate, with potential implications for designing monitoring approaches aimed at fostering stewardship.

1 Introduction

Tipping elements in the Earth System pose urgent global challenges that necessitate sustained international cooperation. This necessitates that global actors, such as countries, major corporations, and cities, collectively adopt long-term mitigation strategies to avert ecological collapse, rather than free-riding for short-sighted gains. This scenario can be understood as a social-ecological dilemma characterized by a feedback loop between collective human actions and the environmental state.

A growing body of research has examined the conditions under which cooperation emerges under the risk of catastrophic climate change [12, 6, 5]. Their findings highlight key drivers of cooperation, including the severity of environmental consequences, the extent to which agents value future rewards, and the certainity of the threshold.

However, a gap exists between the ecosystem's objective state and the limited information available to actors, due to noisy early warning signals [17], uneven awareness [11], and scientific uncertainty in current projections [6]. Together, these factors contribute to a misrecognition of the true climate state; at times, creating the illusion of stability even as it may already be on a path toward degradation.

Climate policy decisions are also shaped by the broader social and political context [9], particularly of contributions made by other actors. Nevertheless, uncertainty persists due to limited transparency regarding countries' mitigation commitments and the implementation of their climate policies [7].

Determining the minimal information requirements for sustaining cooperation is essential for effective stewardship. Whether to prioritize environmental monitoring or social transparency, and under what conditions each is effective is an open policy question requiring clearer answers.

Previous research has begun to address specific aspects of this problem [19]. Barrett and Dannenberg [6] explores how ambiguity about the location of ecological tipping points can discourage contributions, while Abou Chakra et al. [1] investigated strategies that emerge under uncertain risk of collapse. [8, 15] incorporates fairness into agents' utility functions, thus including social dimension. Parks et al. [16], through experimental methods, examine how ecological and static social signals influence cooperative behaviour.

However, we still lack a unified framework that jointly examines how ecological cues and social feedback between interacting agents shape cooperation in a coupled socio-ecological system.

Independent work has highlighted the importance of both information channels: Kleshnina et al. [10] demonstrated that knowledge of the environmental state supports cooperation in dynamic games, while social cues are essential for enabling direct reciprocity, an established mechanism for promoting cooperation [2]. Building on these insights, we hypothesize that combining social and ecological information will foster cooperation more effectively than either alone.

Thus, in our study, we develop an idealized model in which access to social and ecological information is explicitly controlled, allowing us to systematically examine how each type of information influences cooperation and test the hypothesis. The study has three aims: (i) to compare the relative effectiveness of social versus ecological information in fostering cooperation; (ii) to investigate how the two types of information interact (iii) to explore how these effects depend on underlying incentive structures and ecological feedback dynamics.

2 Methods

2.1 Ecological Public Goods Game

Our model is based on the Ecological Public Goods Game (EcoPG) 1. The EcoPG is an extension of the standard public goods game, incorporating a tipping element to capture risk of ecological collapse.

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The actors in the model represent geopolitical units (national, subnational, or supranational entities), engaged in climate policy and decision-making. We consider only 2 agents for simplicity, though it can be extended for larger groups. Agents have only two possible actions Cooperation (C) and Defection (D). Cooperation represents proactive climate measures, including greenhouse gas emissions reductions, investing in carbon sinks, and other sustainability-oriented initiatives. This involves a mitigation cost c, which gets multiplied by the public goods enhancement factor f and is equally distributed to all actors, reflecting the marginal benefits of avoiding *gradual climate change*. This applies in the scenario where the Earth system remains relatively stable, which we call the 'prosperous' state.

Defection, on the other hand, reflects a business-as-usual approach that leads to ongoing emissions and environmental harm. While already socially suboptimal, defection is also associated with probabilistic risk of triggering large-scale systemic collapse, pushing the Earth into a 'degraded state', sometimes referred to as the hothouse Earth scenario. This collapse probability increases marginally with each additional defector (q_c/N per defector).

Once the system enters the degraded state, all actors receive a negative environmental payoff, $m < 0$, irrespective of their actions. However, the recovery probability (of returning to the properous state) is still dependent on number of cooperating actors (increasing q_r/N per defector

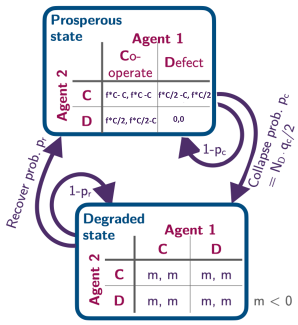


Figure 1: EcoPG for 2 agents. Unless otherwise specified, the parameters are set as follows $f = 1.2$, $c = 5$, $q_c = 0.02$ and $q_r = 0.0001$

For a comprehensive account of the EcoPG model, see [5]

From the perspective of a Markov Decision Process, [18], the environment that the agent finds itself at time t in the EcoPG be described by the social & ecological context. Formally, state of the environment s_t can be given by the tuple $(e_t,\ a_{t-1},\ a'_{t-1})$, where $e_t \in \{p, g\}$ denotes the ecological status (prosperous or degraded respectively), and $a_{t-1},\ a'_{t-1} \in \{C, D\}$ represents the player's and the counterpart's previous actions, respectively.

2.2 *Information Regimes*

We defined ecological information as the agent's knowledge of the current environmental state. That is, in the presence of ecological information, agents can condition their behavior on whether the environment is in a prosperous or degraded state.

Social information was taken as the agent's awareness of the actions taken by others. This means that agents adopt strategies that condition their behavior on past interactions (we restrict our analysis to memory-1 strategies for simplicity, although longer histories are possible) in the presence of social information. In contrast, in the absence of social information, agents rely on memory-0 strategies, which are independent of social feedback.

To implement regimes with varying levels of available social and ecological information, we adopted the framework of partial observability. Here, agents only have access to *observations* i.e. partial signals in place of the system state, which forms the basis of the agent's decisions.

The mapping of environmental state s_t to the observations o_t is unique for each regime and given by the projection function $\omega_r : S \rightarrow O_r$. We assume that observations are deterministic, such that $P(o_t \mid s_t) = \delta^k\left(o_t,\ \omega_r(s_t)\right)$, where δ^k is the Kronecker delta function.

2.3 *Treatments*

We followed a factorial design with four treatments to systematically isolate and assess the effects of social and ecological information, as well as their interaction.

I. **Ecological + Social (Complete):**

$$\omega_{\text{Com}}(e_t, a_{t-1}, a'_{t-1}) = (e_t, a_{t-1}, a'_{t-1}).$$

This results in 8 (4 action histories x 2 ecological condition) distinct observations.

II. **Ecological-Only:**

$$\omega_{\text{Eco}}(e_t, a_{t-1}, a'_{t-1}) = e_t.$$

This yields two possible observations of the state: prosperous (p) and degraded (g).

III. **Social-Only:**

$$\omega_{\text{Soc}}(e_t, a_{t-1}, a'_{t-1}) = (a_{t-1}, a'_{t-1}),$$

resulting in 4 observations: $(C, C), (C, D), (D, C), (D, D)$, corresponding to possible joint actions in the previous round.

IV. **No Information:**

$$\omega_{\text{None}}(s_t) = o_0.$$

All system states map to a single undifferentiated observation, thus agents receive no information about the environment or past actions.

The strategies of an agent i under each information regime are shown below (Table 1). $p^i_C(\cdot)$ denotes the probability of cooperation given the corresponding observational state.

Regime	**Strategy**
Complete Info	$(p^i_C(p, CC),\ \ldots,\ p^i_C(g, DD))$
Ecological-Only	$(p^i_C(p),\ p^i_C(g))$
Social-Only	$(p^i_C(CC),\ p^i_C(CD),\ p^i_C(DC),\ p^i_C(DD))$
No Information	p^i_C

Table 1: Strategy under each information condition

2.4 *Learning Dynamics under Partial observability*

To impose varying degrees of information access across four regimes. Different information treatments using the partial observability framework introduced in [3]. In this setting, an agent forms a posterior belief $B^i(s|o^i)$ over true system states.

$$B^i(s|o^i) = \frac{O(o^i \mid s)\, \sigma^*_X(s)}{\sum_{s'} O(o^i \mid s')\, \sigma^*_X(s')}$$

where $O(o^i \mid s)$ is the likelihood of observing o^i in state s, and $\sigma_x(s)$ is the stationary probability of a state under joint policy X, which serves as a prior. Agents use their posterior beliefs to compute belief-weighted expected rewards and transition probabilities of the observations, which are then incorporated into the actor-critic updates. A detailed justification of the learning dynamics framework with partial observability can be found in [3]

The learning dynamics itself was based on the deterministic limit of the temporal difference reinforcement-learning framework [18]. Specifically, we used the **Actor–Critic** algorithm for the strategy updates: the actor updates policies to favor actions with higher estimated rewards, while the critic updates value-function estimates according to the temporal difference updates. The equations governing the learning dynamics in the deterministic limit are derived in detail in [4]

Simulations

We ran initial simulations for each information regime for $N = 1000$ different initial policies which were sampled via Latin Hypercube Sampling for uniform coverage of the strategy space.

The cooperation probability ($\bar{p}^*_{i,c}$), as an average over the stationary distribution of observational states ($\sigma_X(o)$) and over the two agents.

$$\bar{p}_{i,c} = \frac{1}{2} \sum_i \sum_o p_{i,c}(o)\, \sigma_X(o),$$

The outcomes were classified with the following thresholds that allowed partitioning of the policy space into basins of attraction for cooperative, defective, and mixed strategies, along with a margin of deviation.

$$\text{Outcome} = \begin{cases} \text{Cooperate} & \text{if } \bar{p}_c \geq 0.95, \\ \text{Mixed} & \text{if } 0.05 < \bar{p}_c < 0.95, \\ \text{Defect} & \text{if } \bar{p}_c \leq 0.05. \end{cases} \quad (1)$$

For our preliminary analysis, we ran simulations with a collapse impact of $m = -6$ and a discount factor of $\delta = 0.98$ for each agent, reflecting a severe collapse scenario and moderately high concern for future rewards. This parameter combination was found to correspond to the ‘coordination regime’ of the baseline ecological public goods game, in which both mutual cooperation and mutual defection are Nash equilibria. [5].

We also characterized the resulting strategies and recorded their relative abundances. In the only ecological and complete information, only the strategies in the prosperous state were considered for analysis our focus was on climate change mitigation rather than the interactions in the degraded state.

To better understand the learning dynamics within each information regime, we visualized phase portrait projections. The minimally visible grey flow vectors correspond to individual learning updates under randomly initialized policies. The colored vectors represent the average of these updates, capturing the expected direction of learning. Trajectories for three randomly selected strategies are also shown for reference

[0] The simulation code and supplementary data will be made publicly available upon publication

3 Results

We compared the basins of attraction for cooperation across informational modes to assess the relative importance of different cue types in promoting cooperation, as well as their interaction effects.

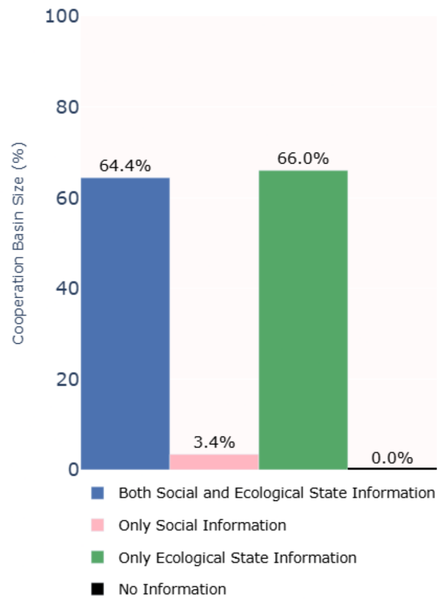
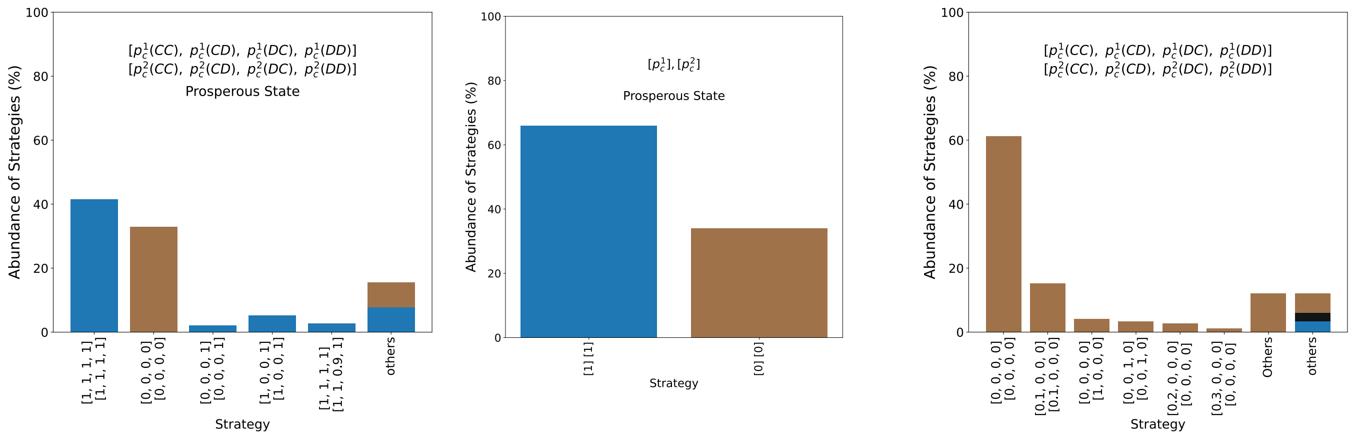


Figure 2: Cooperation Levels Across Each Information Regime

Fig. 2 Cooperation is highest when only ecological information is available. Interestingly, combining social cues with ecological information does not enhance cooperation levels beyond what is acheived with only ecological feedback; instead, a slight antagonistic effect is observed. Social cues alone provide only marginal support for cooperation, with defection remaining dominant. In the absence of both cue types—i.e., when no information is available—the system consistently converges to full defection. Together, these results suggest that ecological state information is both necessary and sufficient for sustaining cooperation, while social information is comparatively less effective

We also note qualitatively distinct strategy profiles under each condition We also observe qualitatively distinct strategy profiles under each condition (Fig.3). Under **complete information** (Fig.3a), cooperative strategies such as $[1, 1, 1, 1]$, $[1, 1, 1, 0.9]$ (ALLC), and $[1, 0, 0, 1]$ (Win-Stay Lose Shift [14]) emerge, along with the defective strategy $[0, 0, 0, 0]$ (ALLD). Other atypical and mixed strategies are seen at low abundance. In the **only-ecological-information (3b)** treatment, the game is equivalent to the baseline public goods gam. As the parameters chosen corresponded to the coordination regime, we had two stable outcomes: converging to full cooperation or full defection in he prosperous state based on initial conditions. Under **social-only information (3c)**, ALLD and mixed strategies closely resembling it are the most abundant. When **no information** is available, all initial conditions uniformly converge to defection.

It is interesting to note that, a stable cooperative Nash equilibrium strategies in Iterated Prisoner’s Dilemma-like games [13] like Win-Stay Lose Shift , emerges only when ecological cues are available



(a) Complete Information (b) Ecological Information (c) Only Social Information

(d) No Information: All initial conditions 100% converged to full defection [0]:[0].

Figure 3: Relative abundance of strategies under different information regimes. $p_c^i(o) \in [0, 1]$ is the probability of cooperation for agent i for observation o. Bars in blue represent cooperative strategies, brown indicate defecting strategies, and black denote mixed strategies, all in accordance with the thresholds defined earlier.1. Note that only the prosperous state strategies are reported for (a) and (c). Only strategies with an abundance greater than 1% are displayed seperatey in the plots; the remaining strategies are grouped under *Others* with the stacked segments indicating composition. Strategy profiles symmetrical across agents are reported as a single entry.

alongside social information under this incentive structure. The presence of mixed strategies of low abundance and other idiosyncratic profiles (e.g., $[0, 1, 0, 0]$, $[0, 1, 0, 0]$) in the 'Complete' and 'Only-Social-Info' treatments is a likely result of non-ergodicity of the partial observability framework that allows non-nash equilirum strategies to persist (specifically, when stationary probability of a state drops to zero)

The phase portrait projections (Fig. 5) further sheds light on the learning dynamics in each regime. Note that only the prosperous state projections are shown for the complete and only ecology information case. When both ecological and social information (Fig.5a) are available we see complex patterns with bistability for c,c, mutual cooperation as the global attractor for d,d and limit cycles when the agent's previous actions were asymmetric. Under ecological-only information (Fig. 5b), the system exhibits bistability in the prosperous consistent with Barfuss et al. [5]. When only social information (Fig 5c) is available, social cues are insufficient to sustain cooperation, and the dynamics converge toward mutual defection, with small local deviations in the flow. Finally, in the absence of information (Fig. 5d), the learning updates are uniformly towards mutual defection, regardless of the initial condition.

3.1 Discussion

Our study establishes information as a major modulator of cooperation in intertemporal collective-risk dilemmas. The results indicate that reliable access to environmental cues is essential for sustained collective action. The stark difference in cooperation levels with and without ecological cues suggests an important insight: cooperation tends to emerge only when agents explicitly model the environmental state, implicit degradation penalties is insufficient to support coopertaion. For the parameter combination analysed, social reciprocity alone contributes little to fostering cooperation, highlighting the limitations of relying solely on immediate social consequences of defection. In fact, it marginally reduces the level of cooperation that emerged in the presence of ecological cues, running counter to our initial hypothesis. These insights can guide the development of better mechanism design for global stewardship. Providing reliable information about the environmental state in the form of local degradation signs, early warnings of tipping points should be prioritised to elicit responsible behaviour. On the other hand, reciprocity-driven enforcement measures, such as international agreements, emissions disclosures, and carbon tariffs, appear less effective in promoting cooperation under the conditions studied. However, these findings are preliminary and warrant further investigation before drawing definitive conclusions.

Nevertheless, this result may depend on the underlying incentive structure. Exploring outcomes under a higher public-good enhancement factor f would therefore be a useful next step. In addition, local stability analysis via small perturbations around the final strategies, would help distinguish true attractors from such idiosyncratic points of convergence thus offering clearer insights into the stratgey outcomes. Simulating the model across a range of parameters, such as the collapse impact m and the discount factor δ, would offer a more comprehensive understanding of the factors shaping cooperation. This could be further complemented by a metagame analysis [5] to analytically derive thresholds for stability under each information regime.

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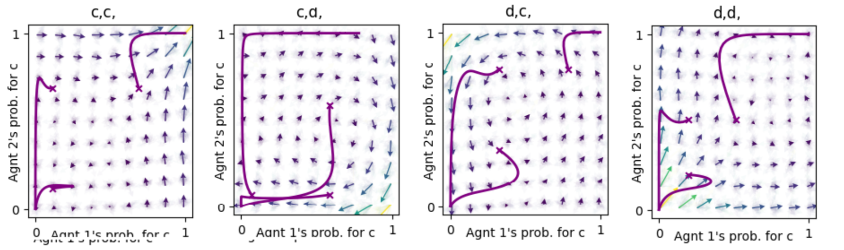
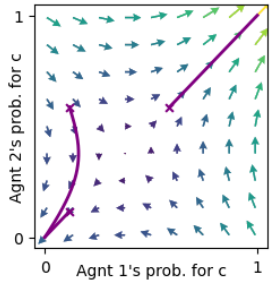
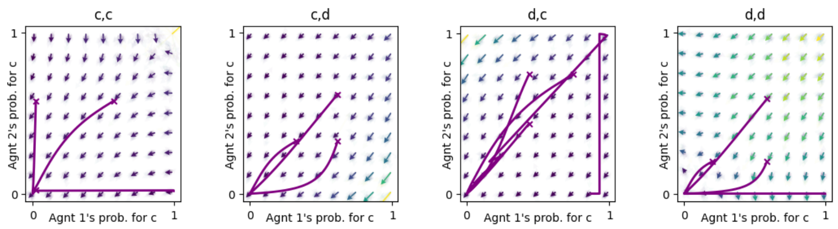


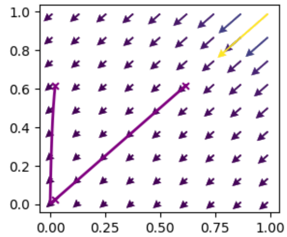
(a) Complete Information



(b) Ecological Information



(c) Only Social Information



(d) No Information

Figure 5: Phase portrait projections for each information regime. Flow arrows represent the average learning update vector. Visual spread in the faint grey vectors are seen when the flow is sensitive to the full strategy profile, and is absent when the flow is independent of the unprojected dimensions. Three trajectories (in purple) are visualized, each starting from a random initial condition marked by a cross.

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