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# Disrespect Others, Respect the Climate? Applying Social Dynamics with Inequality to Forest Climate Models

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## Abstract

Understanding the role of human behavior in shaping environmental outcomes is crucial for addressing global challenges such as climate change. Environmental systems are influenced not only by natural factors like temperature, but also by human decisions regarding mitigation efforts, which are often based on forecasts or predictions about future environmental conditions. Over time, different outcomes can emerge, including scenarios where the environment deteriorates despite efforts to mitigate, or where successful mitigation leads to environmental resilience. Additionally, fluctuations in the level of human participation in mitigation can occur, reflecting shifts in collective behavior. In this study, we consider a variety of human mitigation decisions, in addition to the feedback loop that is created by changes in human behavior because of environmental changes. While these outcomes are based on simplified models, they offer important insights into the dynamics of human decision-making and the factors that influence effective action in the context of environmental sustainability. This study aims to examine key social dynamics influencing society's response to a worsening climate. While others conclude that homophily prompts greater warming unconditionally, this model finds that homophily can prevent catastrophic effects given a poor initial environmental state. Assuming that poor countries have the resources to do so, a consensus in that class group to defect from the strategy of the rich group (who are generally incentivized to continue "business as usual") can frequently prevent the vegetation proportion from converging to 0.

## 1 Introduction

Understanding how human behavior impacts climate change is crucial for mitigation efforts and scenario planning [1, 2, 3, 4, 5], and averting potential climate catastrophe. Many pre-existing models have been built in order to parse out important relationships such as those between vegetation and mitigative action [6], temperature and income inequality [7], perceived environmental risk and mitigative action [8], and others. Given the plethora of parameters and assumptions baked into each of these models, applicability to the real world climate system is always considered as one of the primary benchmarks. Creating a simplified model which synthesizes many of the important components of previous theoretical models is hence seen as an optimal way to minimize potential errors in parameterization and instead draw broad generalizations from many initial states.

Investigations of climate change solutions have taken many forms. Many studies have focused in developing climate projections from real world climate data, from over the last 20,000 years [9, 10, 11, 12, 13]. This has led to the creation of incredibly complex and increasingly robust Earth-systems models [14]. In terms of investigating possible climate solutions, evolutionary game theory is commonly used to model important social dynamics [15, 16]. Many have treated climate action as a social cooperation game to avoid catastrophic results [17, 18, 19, 20, 21, 22, 23]. Some have even prioritized experimental designs [24]. In many cases, these models involve interaction and feedbacks between human activity and the environmental state [25, 26, 27, 28]. While social-climate dynamics are a growing topic of study, the existent literature on inequality in these dynamics still is relatively scarce [7, 29, 30].

Using a forest dieback model coupled to a homogeneous population, [6] finds a limited number of stable fixed-points (varying depending on the initial temperature conditions), signifying a limited number of potential vegetative outcomes in equilibrium. This simplified model already limits the number of potential climate futures, but assumes homogenized incentives within the population, rather than allowing different individuals or groups to face different incentives to mitigate climate change. [7] accounts for population differences and dynamics. Modeling populations as divided into rich and poor groups (with interactions in between), they find through an Earth-systems model that increasing homophily (how much individuals want to only interact within their own group) increases peak temperature anomaly, regardless of initial environmental conditions. Given polarization on current climate issues, accounting for differing incentives is critical to understanding how to maximize engagement in mitigative efforts.

In the study of social-climate models, interpretability is key [31, 32, 33, 34]. While a variety of Earth-systems models may more accurately represent the conditions governing our climate system, simplified models offer improved interpretability and enable parameter variation to highlight key relationships. Hence, this study primarily couples the two strong points of the methods explained above: an easily interpretable forest-dieback vegetative model with more robust social dynamics to account for pervasive societal inequalities. The rest of the paper will proceed as follows. Section 2 contains a discussion of our model design, section 3 describes first the main results of our simulations as well as additional robustness checks for our model. Section 4 then summarizes our findings and offers perspectives for further research.

## 2 Methods and Model

### 2.1 Vegetation Model

Discussions of forest dieback models frequently are centered around discussion of the Amazon rainforest, a critical marker for climate health [35]. We represent the vegetation coverage,  $v$ , as a proportion between 0 (barren, no coverage) and 1 (lush, full coverage), where  $v$  is governed by the following equation:

$$\frac{dv}{dt} = gv(1 - v) - \gamma v \quad (1)$$

Here,  $g$  is the growth rate, and  $\gamma$  is the decay, or disturbance rate. As in [35],  $\gamma = 0.2$ . As growth of plants depends on how proliferated the plant already is, the growth rate  $g$  is governed by the equation seen below:

$$g = g_0 \left[ 1 - \left( \frac{T - T_{opt}}{\beta} \right)^2 \right] \quad (2)$$

Where  $g_0 = 2$  is the maximum growth rate,  $T_{opt} = 28^\circ\text{C}$  is the optimal temperature for vegetation growth, and  $\beta = 10$  is the half-width of the growth versus temperature curve [6]. Finally,  $T$  represents the actual temperature, and is represented as follows:

$$T = T_v + (1 - v)a. \quad (3)$$

Importantly,  $T_v$  represents the temperature under full forest coverage conditions. Additionally,  $a = 5$  represents the difference between surface temperatures in barren and completely forested regimes—that is, the temperature cost of losing all vegetation in the forest.

[6] contains a detailed explanation of this forest model in isolation, so we will postpone further discussion of the vegetation model to subsection 2.3, where the coupling with the social dynamic model will be detailed.

### 2.2 Social Dynamics Model

As in [6], [7], and others concerning public goods games [36, 26, 23], this study considers a population deciding between two possible actions: mitigation ( $M$ ) and non-mitigation ( $N$ ). As in [7], this study for simplicity creates a population divided into two groups, which for convenience are called “rich” ( $R$ ) and “poor” ( $P$ ). These two groups differ in terms of the costs required to engage in mitigative action, the income they have to be able to engage in mitigative actions, their level of satisfaction with the climate, and size in the entire population. Additionally, between-group interaction is governed by a homophily term, representing the relative value which a player puts on the actions of those in the opposing group compared to those in the same group. This term will be notated as  $h$ . When  $h = 0$  (no homophily), players value the actions of the opposing group equally to those of the people in their own group. When  $h = 1$  (high homophily), players place no value on the actions of the opposing group and instead only place value on the actions of their own group.

Let the subscript  $i \in \{0, 1\}$  denote the class group, where  $i = 0$  indicates the rich group and  $i = 1$  indicates the poor group. Subscripts  $R$  and  $P$  will be used in later sections for clarity. For a given value of  $i$ ,  $j = 1 - i$  denotes the opposing group. For group  $i$ ,  $x_i$  represents the proportion of mitigators in that group while  $y_i = 1 - x_i$  represents the proportion of non-mitigators. The payoffs for the group  $i$  are

$$E_i(M) = -\alpha_i + \frac{1}{2}f(T_f) + \delta[x_i + (1 - h)x_j] \quad (4)$$

for mitigators and

$$E_i(N) = -\frac{1}{2}f(T_f) + \delta[y_i + (1 - h)y_j] \quad (5)$$

for non-mitigators [7].  $\alpha_i$  represents the costs of mitigation for group  $i$ ,  $\delta = 1$  represents the strength of social norms,  $h$  is the homophily term described above, and  $x_j$  represents the proportion of people in the opposing group who are mitigators. Finally,  $f(T_f)$  is a sigmoid function representing the personal cost of global warming, and is represented by the following equation<sup>1</sup>

$$f(T_f) = \frac{f_{\max}}{1 + e^{-w[-7.5v(t) + 7.5v(t-10) - T_c]}} \quad (6)$$

Here,  $f_{\max}$  is the perceived maximum warming cost,  $w$  is the perceived nonlinearity of warming cost,  $v(t)$  is the vegetation proportion at time  $t$  (more simply, the currently perceived vegetation),  $v(t - 10)$  is the perceived vegetation proportion ten years ago, and  $T_c$  is the maximum temperature rise which can be tolerated by individuals, from here on called the critical temperature<sup>2</sup>. As explained by [7], this cost is designed to be an explicit incentive to mitigate and a disincentive to not mitigate (a social benefit/cost), while the material costs of climate change would impact mitigators and non-mitigators equally within groups.

Following the derivations of [7], we obtain the following replicator dynamics

$$\frac{dx_i}{dt} = \kappa x_i y_i [E_i(M) - E_i(N)] + (1 - h)\kappa \{x_j \max[E_j(M) - E_i(N), 0]y_i - y_j \max[E_j(N) - E_i(M), 0]x_i\} \quad (7)$$

Here,  $\kappa = 0.05$  represents the social learning rate, or how quick players are to change their opinions based on perceived information.

### 2.3 Coupled Social-Climate Model

While we divided the mitigation proportions into two groups,  $x_R$  and  $x_P$ , from an environmental perspective the total mitigation effort, regardless of social divisions, is most important. To get the total mitigation proportion  $x$ , we define the following relation

$$x = \min\{s\rho x_R + (1 - \rho)x_P, 1\} \quad (8)$$

Here  $\rho = 0.25$  represents the proportion of the total population which is in the rich group. Additionally,  $s \geq 1$  represents the relative effectiveness of mitigative action for the rich group. Not only might the rich group have lower costs to mitigating, but the opportunity for technological advancement implies that the rich group may be able to provide greater environmental benefit with less collective effort (corresponding to a larger  $s$  value).

Following [6]'s aim of adding a term  $\eta(x)$  to the growth rate in the vegetative dynamics which increases monotonously as the total proportion of mitigators increases, this study sets  $\eta(x) = 0.2 + 0.4x$  and multiply to equation (2) to get

$$g = g_0 \left[ 1 - \left( \frac{T - T_{opt}}{\beta} \right)^2 \right] \eta(x) \quad (9)$$

Plugging in the parameters as described above for all values except  $T_v$ , we get

$$\frac{dv}{dt} = 2[1 - 0.01(T_v - 23 - 5v)^2](0.2 + 0.4x)v(1 - v) - 0.2v \quad (10)$$

Hence, this study define the coupled delay differential equation system of three equations as follows

<sup>1</sup>See [6] for a full derivation of this equation.

<sup>2</sup>We investigate the sensitivity of the results to the values of  $f_{\max}$  and  $w$  in section 3.4. When otherwise not specified,  $f_{\max} = 5$  and  $w = 3$ .

$$\begin{cases}
\frac{dv}{dt} = 2[1 - 0.01(T_v - 23 - 5v)^2](0.2 + 0.4x)v(1 - v) - 0.2v & \text{(i)} \\
\frac{dx_R}{dt} = \kappa x_R y_R [E_R(M) - E_R(N)] + (1 - h)\kappa \\
\quad \{x_P \max[E_P(M) - E_R(N), 0]y_R - y_P \max[E_P(N) - E_R(M), 0]x_R\} & \text{(ii)} \\
\frac{dx_P}{dt} = \kappa x_P y_P [E_P(M) - E_P(N)] + (1 - h)\kappa \\
\quad \{x_R \max[E_R(M) - E_P(N), 0]y_P - y_R \max[E_R(N) - E_P(M), 0]x_P\} & \text{(iii)}
\end{cases} \quad (11)$$

### 3 Results

To complete the necessary simulations, we first perform a spin up period of 10 years with the vegetative level using the uncoupled model seen in equation (1). Then for years 10-200, this study simulates using the delayed differential equation system of equation (11). Simulations were performed with the ddeint package in Python.

#### 3.1 Stability Analysis

To get a sense of how the system of equations depends on the homophily term, phase portraits were developed over varying levels of homophily, seen in figure 1. While [6] finds a number of fixed points which vary by the temperature parameters, this study also finds that the stability of the system depends on the homophily level. Here the blue planes represent nullclines of the vegetation proportion  $v$ , red the proportion of poor mitigators  $x_P$ , and green the proportion of rich mitigators in the population  $x_R$ . The equilibrium points to our system of equations exist at the intersections of these three planes, and the arrows seen within the plots indicate the direction of movement of the system to a given fixed point. Given the shape of the  $x_P$  nullclines, one can begin to see an uneven weighting of opinions between the rich and poor groups. When  $h = 1$ , there is a (vertical) nullcline at  $x_P = 1$ , while at the other values shown, this sheet is only seen at a very high level of  $x_R$ . When  $h < 1$ , the poor group requires a large mitigative effort from the rich group in order to converge to a high mitigation proportion themselves. On the international stage, many small nations opt to follow the directives of global powers; hence our model appears to capture a similar phenomenon. Due to the complexity of the system of equations, a simple closed-form solution to all three equations is not possible without significant parameterization. However, one can notice an identical shape for the  $v$  nullclines as those seen in [6] in all three phase portraits when looking on the  $v - x_P$  plane.

#### 3.2 Case 1: Increasing Homophily Worsens Environmental Outcomes

[7] find unambiguously that increasing the homophily parameter increases peak temperature anomaly in their earth systems model. In the coupled forest dieback model, we find analogous results given particular underlying conditions. Figure 2 shows a heatmap, where the color scheme represents the vegetation proportion after simulating for 200 years for given values of  $T_v$  (horizontal axis) and  $T_c$  (vertical axis). The dark brown regions represent simulations where the

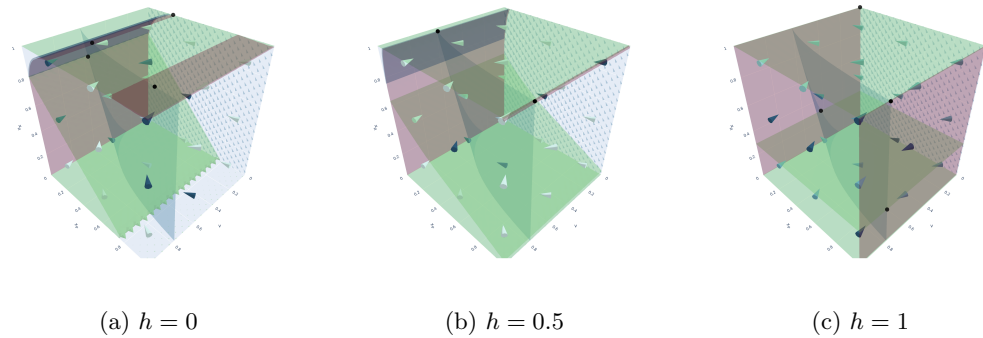


Figure 1: Phase Portraits over Varying Levels of Homophily.

Notes: The above figures depict phase portraits of the system of equations over three different levels of homophily ( $h$ ). Figure 1a depicts the system with no homophily, understood as no bias towards one's own groups. Figure 1b depicts the system under a moderate amount of homophily ( $h = 0.5$ ), while figure 1c depicts the system under full homophily ( $h = 1$ ). Black dots represent stable fixed points of the system of equations. The blue planes represent the  $v$  nullclines, the red planes represent the  $x_P$  nullclines, and the green planes represent the  $x_R$  nullclines. The multicolored arrows in the plot represent directions of movement of the system.  $T_v = 30$  and  $T_c = 0.5$ .

vegetation has completely died out, while the light green color represents a larger vegetation proportion after the 200 year simulation period. When  $h = 0$ , there exists a large range of  $T_v$  and  $T_c$  values which result in a very high vegetation proportion, around 0.8. However, when  $h = 1$ , this region becomes very small, and most  $T_v$  and  $T_c$  values result in a vegetation proportion around 0.5.

Interestingly, figure 2a closely mirrors figures seen in [6]. This has two main implications. Firstly, the deterministic models seen here and in [6] allow for very few unanticipated outcomes. [6], considering both the vegetation proportion and the mitigation proportion, occasionally (but rarely) find outcomes that seem unintuitive (where the forest survives but no one is a mitigator) or the nature of the system (where convergence is not achieved after 200 years). The system here also does not support oscillatory equilibria, so the presence of oscillations suggests some transients take longer than the 200 year simulation period to converge. However, such cases are not found in our results.

The other main implication stems from the nature of the system of equations itself. When  $h = 1$ , dynamics very close to the more simplistic dynamics seen in [6] are obtained. However, it is when  $h = 0$  when the similar results can be seen. This implies that removing homophily from the system results in a convergence of opinions, resulting in a uniform population like the one analyzed in [6]. While under this set of parameters an agreement to mitigate is reached among the population, we will later see that agreement is not always reached in favor of mitigation.

Figure 3 presents the changes over time of the main parameters of interest,  $x$ ,  $x_R$ ,  $x_P$ , and  $v$ , given particular values of  $T_v$  and  $T_c$ . Here, one can clearly see that prohibiting inter-group discussion results in the group with less to lose from climate change (the rich group) lacking the appropriate social push to participate in mitigative activities. Figure 3a shows the scenario without homophily, while figure 3b displays the time trends under a population with total homophily. As one would expect, the convergence of opinions to agreeing upon maximum mitigation efforts

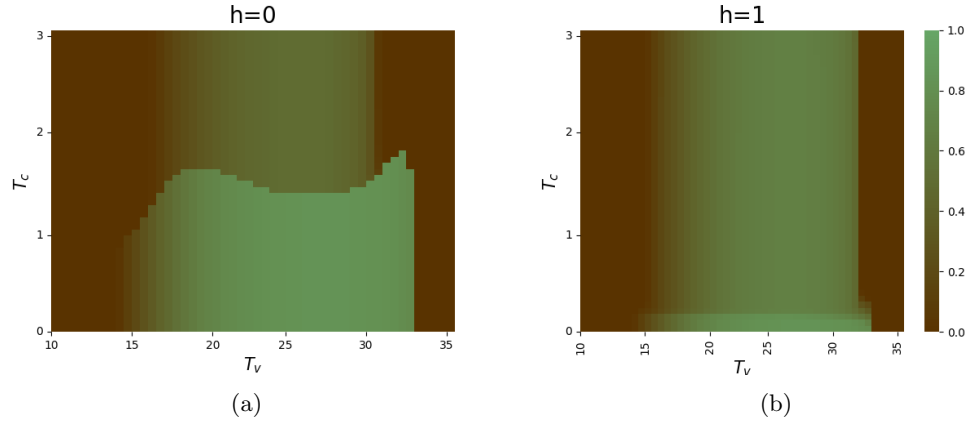


Figure 2: Final Forest Coverage Under Favorable Conditions For Mitigation

Notes: The above figures depict heatmaps of forest coverage  $v$  after 200 years under different ambient temperature  $T_v$ , critical temperature  $T_c$ , and homophily level  $h$ . Figure 2a depicts the long term vegetative outcomes when  $h = 0$ , while figure 2b depicts the long-term outcomes when  $h = 1$ . To define a regime where mitigation is favored, the perceived cost of climate change is high ( $f_{\max} = 6$ ), while the cost of expressing dissatisfaction over the state of the climate is low ( $d = 1$ ).  $v_0 = 0.1$ ,  $x_{R_0} = 0.1$ ,  $x_{P_0} = 0.8$ .

( $h = 0$ ) results in a better environmental state in the long-run.

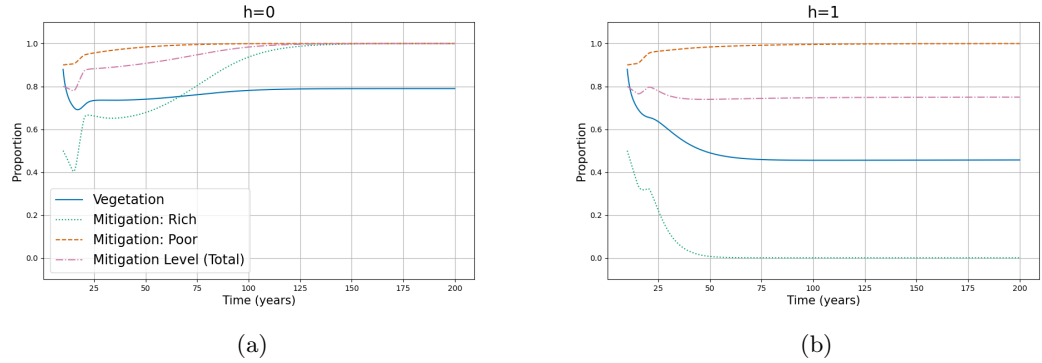


Figure 3: Trajectories Over Time Under Favorable Conditions For Mitigation

Notes: The same initial vegetative state and mitigation proportions under different levels of homophily. Figure 3a shows the values of vegetation  $v$ , the mitigation proportions for the rich and poor groups,  $x_R$  and  $x_P$ , respectively, as well as the total mitigation proportion,  $x$ , when  $h = 0$  over the course of the 200 year simulation period. Figure 3b shows the values of these same variables when  $h = 1$ .  $v_0 = 0.5$ ,  $x_{R_0} = 0.5$ ,  $x_{P_0} = 0.9$ , and the cost of expressing climate dissatisfaction,  $d = 1.5$ .

### 3.3 Case 2: Increasing Homophily Improves Environmental Outcomes

Although the rich group is smaller in population size, its greater access to resources could give it greater influence on the climate through policies and technology, similar to real-world socioeconomic dynamics [37, 38, 39]. Figures 4 and 5 depict patterns consistent with this disproportionate influence of the rich players. As seen in figure 4, increasing homophily reduces the sensitivity of the final vegetation level to the critical temperature. Comparing figures 4a and 4b, one can see a greater final vegetation proportion notably for critical temperature values greater than  $1^\circ\text{C}$ . This implies that under low homophily, a society who is on average less sensitive to temperature rises will neglect climate action, leading to a worse environmental state. However, under high homophily, the group who has more to lose from a deteriorated climate are able to

undertake mitigative actions on their own, leading a better climate outcome.

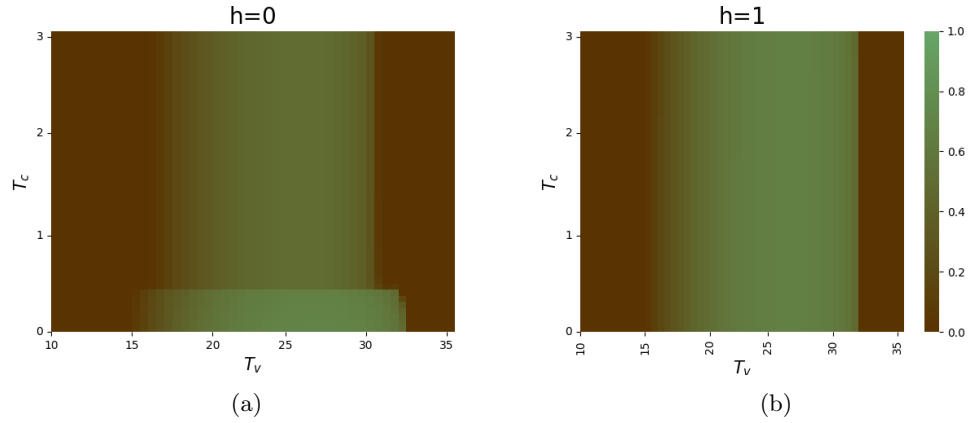


Figure 4: Final Forest Coverage Under Unfavorable Conditions For Mitigation

Notes: The above figures depict heatmaps of forest coverage  $v$  after 200 years under different ambient temperature  $T_v$ , critical temperature  $T_c$ , and homophily level  $h$ . Figure 4a depicts the long term vegetative outcomes when  $h = 0$ , while figure 4b depicts the long-term outcomes when  $h = 1$ . To define a regime where mitigation is originally not favored, the perceived cost of climate change is low ( $f_{\max} = 4$ ), while the cost of expressing dissatisfaction over the state of the climate is high ( $d = 10$ ).  $v_0 = 0.1, x_{R_0} = 0.1, x_{P_0} = 0.8$ .

Additionally, figure 5 paints a clearer picture of homophily stabilizing the vegetation levels. Figure 5a presents a simulation with low homophily. Here, lacking intergroup bias results in the poor group taking a stance of inactivity, alongside the rich group. However, in figure 5b, the high level of homophily results in poor group collusion to undertake mitigative actions, without the influence of the rich group. This subpopulation agreement in turn results in a vegetation proportion stabilizing well above 0, at about 0.45. Like was seen in the phase portraits, the tendency of the rich group to exert influence in low-homophily settings results in actions that more closely match only their incentives: accounting for greater homophily allows the poor group to collectively organize.

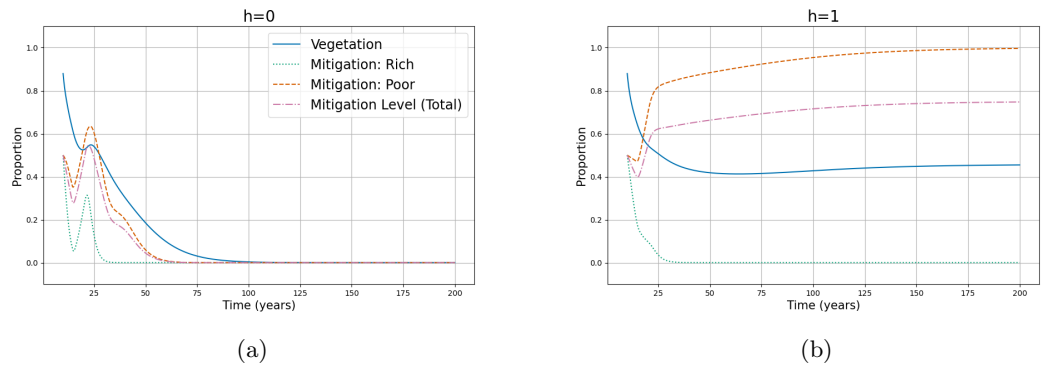


Figure 5: Trajectories Over Time Under Unfavorable Conditions For Mitigation

Notes: The same initial vegetative state and mitigation proportions under different levels of homophily. Figure 5a shows the values of vegetation  $v$ , the mitigation proportions for the rich and poor groups,  $x_R$  and  $x_P$ , respectively, as well as the total mitigation proportion,  $x$ , when  $h = 0$  over the course of the 200 year simulation period. Figure 5b shows the values of these same variables when  $h = 1$ .  $v_0 = 0.1, x_{R_0} = 0.5, x_{P_0} = 0.5$ , and the cost of expressing climate dissatisfaction,  $d = 5$ .

One key finding to note is that negative climate outcomes can be avoided without complete participation in mitigative efforts. Although this has not been a focus of social-climate dynamic



research, many climate activist groups have stressed the importance of smaller actions taken by regional or subnational groups [40, 41]. This paper hence provides additional support to such forms of sectarian climate action.

### 3.4 Alternative Parameter Sweeps

To check the robustness of the results to many of the underlying parameters, this study performed additional simulations to gauge how the underlying social conditions, rather than simply temperature outcomes, impact the final vegetation proportion.

**3.4.1 The Impact of Technological Improvements** Figure 6 investigates the relationship between costs of mitigation and mitigative technologies. What is particularly interesting here is that as the relative effectiveness of mitigative technology (the mitigative effort from the rich group) increases, the rich group only chooses to mitigate (leading to the light green area) when they are given a lower relative cost of mitigation. The sentiment in favor of each country “doing their own share” has been seen gaining traction in current discourse. Hence, this further highlights the divide in incentives between rich and poor groups when it comes to mitigative activity.

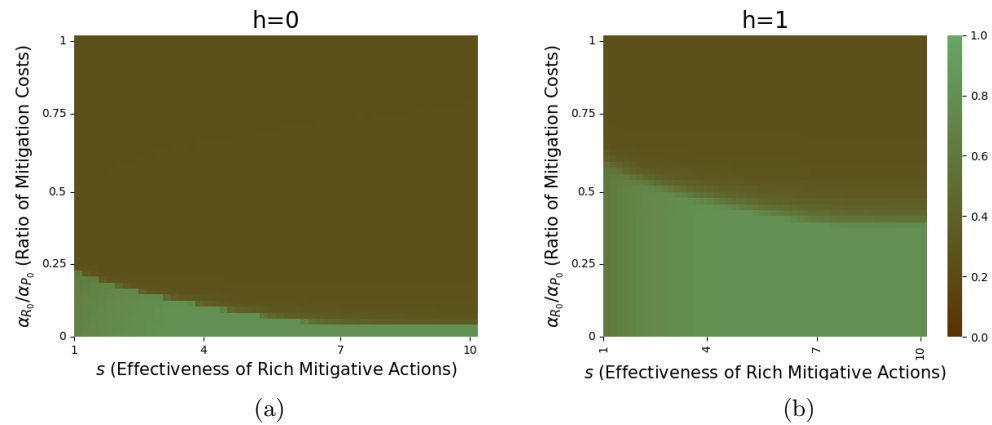


Figure 6: Final Forest Coverage Allowing For Technological Improvements

Notes: The above figures depict heatmaps of forest coverage  $v$  after 200 years under different relative mitigation costs for the rich group ( $\alpha_{R0}/\alpha_{P0}$ ), effectiveness of mitigation from the rich group  $s$ , and homophily levels  $h$ . Figure 6a depicts the long term vegetative outcomes when  $h = 0$ , while figure 6b depicts the long-term outcomes when  $h = 1$ . An increase in  $s$  can be understood as improvements in mitigative technology which belong exclusively to the rich group, but provide benefit to all individuals.  $T_v = 30, T_c = 0.5, v_0 = 0.1, x_{R0} = 0.5, x_{P0} = 0.5$ .

**3.4.2 The Cost and Immediacy of Warming Effects** To analyze how people responded to their perceived effects of climate change (not merely the observed state of the forest), this study compared the maximum warming cost to the nonlinearity of warming costs. Figure 7 clearly shows much greater robustness of the system to greater warming costs or nonlinearity effects in regimes with greater homophily. In the no homophily regime (figure 7a), players must experience a very large warming cost - and have that cost be incurred rather slowly - to be incentivized enough to mitigate and avoid climate catastrophe. However, in the high homophily regime (figure 7b), these



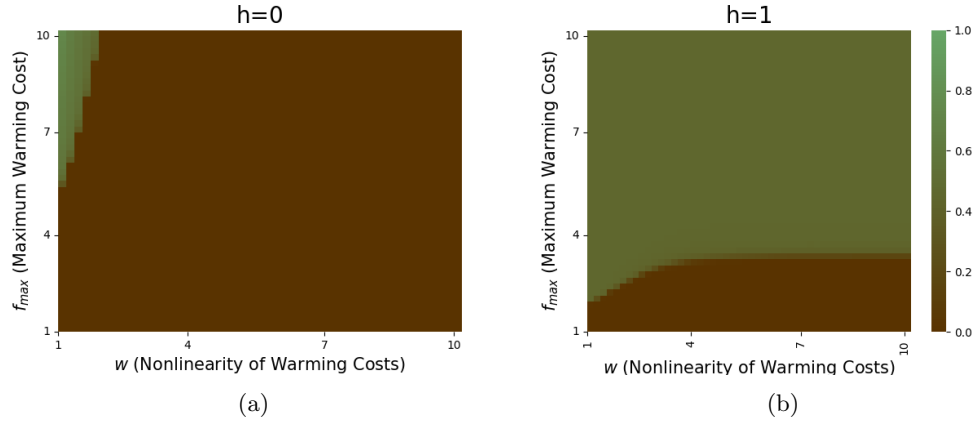


Figure 7: Final Forest Coverage Under Changing Cost and Immediacy of Warming Effects

Notes: The above figures depict heatmaps of forest coverage  $v$  after 200 years under different nonlinearity of warming costs  $w$ , maximum warming costs  $f_{\max}$ , and homophily levels  $h$ . Figure 7a depicts the long term vegetative outcomes when  $h = 0$ , while figure 7b depicts the long-term outcomes when  $h = 1$ .  $T_v = 31.5, T_c = 1.5, v_0 = 0.1, x_{R_0} = 0.5, x_{P_0} = 0.5$ .

barriers are almost completely removed, allowing people to act while perceiving “weaker” climate impacts much more quickly.

Our model exhibits a potentially counterintuitive effect. While it might be natural to encourage immediate action minimizing warming, figure 7 suggests that such activism (increasing the perceived nonlinearity of warming costs) actually reduces the range of scenarios where a positive climate outcome is achieved. To analyze this further, we must consider our warming function. When  $-7.5v(t) + 7.5v(t - 10) < T_c$ ,  $-w[-7.5v(t) + 7.5v(t - 10) - T_c] > 0$ . In this scenario, increasing  $w$  decreases  $f(T_f)$  in equation (6). For this relation to hold,  $v(t) - v(t - 10) > -\frac{2T_c}{15}$ . For the results shown in figure 7, this means that  $v(t) - v(t - 10) > -0.2$ , or that the vegetation does not decay by more than 0.2 over 10 years. While the sigmoid function is allowed to “flip” throughout our simulations, these results suggest that for most of the years of the simulation, the inequality  $v(t) - v(t - 10) > -0.2$  holds.

**3.4.3 Costs of Mitigation and Social Norms** When discussing strategies to combat climate change, two of the most frequently mentioned pathways involve investments in green energy and working to change societal opinions on a warming planet. Hence, we examine these factors simultaneously, comparing regimes under different levels of homophily. The results are shown in figure 8.

Unsurprisingly, the results of these simulations are highly sensitive to homophily: homophily is strongly correlated to the relevance of social norms. In figure 8b, note that as the strength of social norms increases, the ratio of mitigation costs between rich and poor groups is allowed to decrease. While this could imply either a decrease in costs for the rich group or an increase in costs for the poor group, given figures such as figure 5, the most accurate interpretation is an increase in costs for the poor group, as they are the group more motivated/incentivized to mitigate. This is an

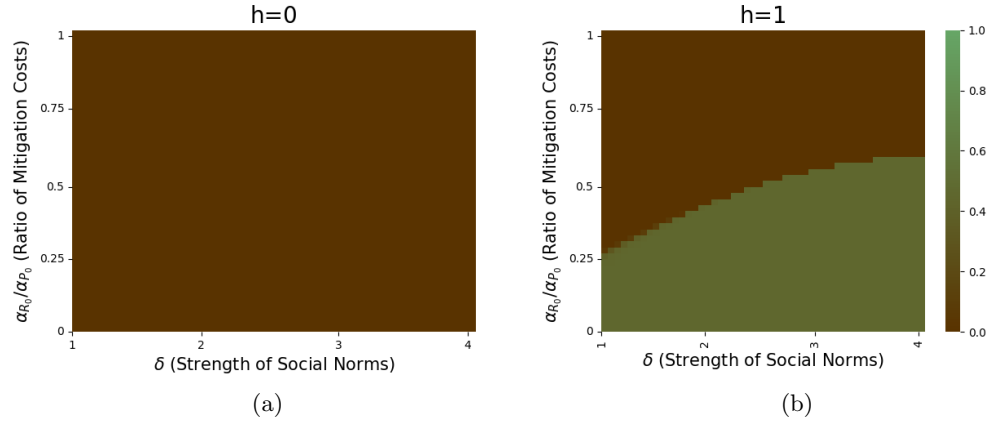


Figure 8: Final Forest Coverage Under Changing Cost of Mitigation and Social Norms

Notes: The above figures depict heatmaps of forest coverage  $v$  after 200 years under different relative mitigation costs for the rich group ( $\alpha_{R_0}/\alpha_{P_0}$ ), social norm strength  $\delta$ , and homophily level  $h$ . Figure 8a depicts the long term vegetative outcomes when  $h = 0$ , while figure 8b depicts the long term outcomes when  $h = 1$ .  $T_v = 31.5, T_c = 1.5, v_0 = 0.1, x_{R_0} = 0.5, x_{P_0} = 0.5$ .

encouraging but not unsurprising result, as individuals feel a greater sense of social responsibility, they are also willing to initiate more monetary support for climate-friendly goals.

#### 4 Conclusion

Collective action is critical to minimizing climate damages [22]. While natural inclination leads us to assume that promoting minimum homophily is the way to get us there, this study shows that this is not always the case. When a group has little to no incentive to mitigate (as is the case with the rich group, who bears little of the costs of climate inaction), dialogue may be futile. Coupling a forest dieback model [6] with more robust population dynamics [7], we see that the rich group's inaction drags down the poor group's mitigation proportion when communication is open between the two groups ( $h = 0$ ). However, because the poor group bears more of the costs of mitigation, it is commonly in their best interests to mitigate. In this case, creating an “echo chamber” through high homophily ( $h = 1$ ) promotes collective climate action among the poor group, which results in more vegetative states.

Additionally, improving a sense of social responsibility for all players unsurprisingly increases the range of climate scenarios preserving some level of vegetation. Furthermore, technological improvements actually increase the range of barren climate scenarios, casting doubt on technological improvements being able on their own to lead to lasting warming mitigation (because they fail to address underlying motivations to mitigate).

Comparing regimes, it is clear that there are thresholds where crossing over results in movement between a green and a barren regime. Analyzing the parameter models in this theoretical system does not necessarily lend itself to direct physical interpretations, but [35] and others do find evidence for tipping points of such systems. This model, while not directly investigating tipping points, nonetheless clearly finds evidence for them, as there are drastic differences in vegetative

outcomes after the 200 year simulation period due to small changes in the underlying parameters.

While this model currently assumes that players accurately understand climate dangers and impacts, a further investigation of individual perception of risk [42], and how that changes in relation to a changing climate, would make this model more robust to changing sentiments as well as a changing climate. Additionally, further analysis of tipping points and overshooting climate targets is another related detail which should be investigated further in this context.

In sum, we study a social-climate system model that incorporates into the die-back forest model with groups of individuals whose mitigation behavior is influenced by social factors including wealth inequality and homophily. We determine dynamic regimes that lead to either successful mitigation or failure to prevent climate disasters. Our proof-of-concept model sheds light on understanding how the intrinsic nonhomogeneity of human societies, from ‘the poor vs the rich’ [43] to ‘us vs them’ [44], shapes behavior and attitudes in collective-risk dilemmas beyond climate change [45, 17, 21].

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### Author contributions

L.W.: Conceptualization, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft; T.Z.: Conceptualization, Investigation, Methodology, Project administration, Supervision, Writing – review & editing; F.F.: Conceptualization, Supervision, Writing – review & editing.

### Data availability

The code used to create the simulations in this paper can be found at the following link:

<https://github.com/dartmouth/SocialClimateDynamics>.

### Supplementary data

This article has no additional data. All relevant data has been included in the main text.

### References

- [1] Syukuro Manabe and Richard T Wetherald. The effects of doubling the co2 concentration on the climate of a general circulation model. *Journal of Atmospheric Sciences*, 32(1):3–15, 1975.

- [2] Klaus Hasselmann. Stochastic climate models part i. theory. *tellus*, 28(6):473–485, 1976.
- [3] Thomas M Bury, Chris T Bauch, and Madhur Anand. Charting pathways to climate change mitigation in a coupled socio-climate model. *PLoS computational biology*, 15(6):e1007000, 2019.
- [4] Frances C Moore, Katherine Lacasse, Katharine J Mach, Yoon Ah Shin, Louis J Gross, and Brian Beckage. Determinants of emissions pathways in the coupled climate–social system. *Nature*, 603(7899):103–111, 2022.
- [5] Bence Bago, David G Rand, and Gordon Pennycook. Reasoning about climate change. *PNAS nexus*, 2(5):pgad100, 2023.
- [6] Longmei Shu and Feng Fu. Determinants of successful mitigation in coupled social-climate dynamics. *Proceedings of the Royal Society A*, 479(2280), 2023.
- [7] Jyler Menard, Thomas M. Bury, Chris T. Bauch, and Madhur Anand. When conflicts get heated, so does the planet: coupled social-climate dynamics under inequality. *Proceedings of the Royal Society B*, 288(1959), 2021.
- [8] Linjie Liu, Xiaojie Chen, and Attila Szolnoki. Coevolutionary dynamics via adaptive feedback in collective-risk social dilemma game. *eLife*, 12:e82954, may 2023.
- [9] Pascale Braconnot, Sandy Harrison, Masa Kageyama, et al. Evaluation of climate models using palaeoclimatic data. *Nature Climate Change*, 2:417–424, 2012.
- [10] Patricia Anderson, O. Bermike, N. Bigelow, J. Brigham-Grette, Mathieu Duvall, Mary Edwards, Bianca Fréchette, Svend Funder, S. Johnsen, Jochen Knies, R. Koerner, Lozhkin Anatoly, J. Matthiessen, Glen MacDonald, G. Miller, M. Montoya, Daniel Muhs, B. Otto-Bliesner, and A. Velichko. Last interglacial arctic warmth confirms polar amplification of climate change. *Quaternary Science Reviews*, 25, 07 2006.
- [11] Franck Bassinot, Charline Marzin, P. Braconnot, Olivier Marti, E. Mathien-Blard, Lombard Fabien, and Laurent Bopp. Holocene evolution of summer winds and marine productivity in the tropical indian ocean in response to insolation forcing: data-model comparison. *Climate of the Past*, 7, 07 2011.
- [12] Jennifer Marlon, Patrick Bartlein, Christopher Carcaillet, Daniel Gavin, Sandy Harrison, Philip Higuera, Fortunat Joos, Mitchell Power, and I. Prentice. Climate and human influences on global biomass burning over the past two millennia (vol 1, pg 697, 2008). *Nature Geoscience*, 2:307–307, 04 2009.
- [13] Jed Kaplan, Nancy Bigelow, Ian Prentice, Sandy Harrison, Patrick Bartlein, Torben Røjle Christensen, Wolfgang Cramer, Nadya Matvedeyeva, A. McGuire, David Murray, Volodya

- Razzhivin, Benjamin Smith, david walker, Patricia Anderson, Andrei Andreev, Linda Brubaker, Mary Edwards, and Lozhkin Anatoly. Climate change and arctic ecosystems: 2. modeling, paleodata-model comparisons, and future projections. 01 2003.
- [14] Philippe Lucas-Picher, Daniel Argüeso, Erwan Brisson, Yves Trambly, Peter Berg, Aude Lemonsu, Sven Kotlarski, and Cécile Caillaud. Convection-permitting modeling with regional climate models: Latest developments and next steps. *WIREs Climate Change*, 12(6):e731, 2021.
- [15] Xiaojie Chen and Attila Szolnoki. Punishment and inspection for governing the commons in a feedback-evolving game. *PLoS computational biology*, 14(7):e1006347, 2018.
- [16] Luo-Luo Jiang, Zhi Chen, Matjaž Perc, Zhen Wang, Jürgen Kurths, and Yamir Moreno. Deterrence through punishment can resolve collective risk dilemmas in carbon emission games. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 33(4), 2023.
- [17] Wolfram Barfuss, Jonathan F Donges, Vitor V Vasconcelos, Jürgen Kurths, and Simon A Levin. Caring for the future can turn tragedy into comedy for long-term collective action under risk of collapse. *Proceedings of the National Academy of Sciences*, 117(23):12915–12922, 2020.
- [18] Zhen Wang, Marko Jusup, Hao Guo, Lei Shi, Sunčana Geček, Madhur Anand, Matjaž Perc, Chris T Bauch, Jürgen Kurths, Stefano Boccaletti, et al. Communicating sentiment and outlook reverses inaction against collective risks. *Proceedings of the National Academy of Sciences*, 117(30):17650–17655, 2020.
- [19] Luke Kemp, Chi Xu, Joanna Depledge, Kristie L. Ebi, Goodwin Gibbins, Timothy A. Kohler, Johan Rockström, Marten Scheffer, Hans Joachim Schellnhuber, Will Steffen, and Timothy M. Lenton. Climate endgame: Exploring catastrophic climate change scenarios. *Proceedings of the National Academy of Sciences*, 119(34):e2108146119, 2022.
- [20] A. Kruczkiewicz, J. Klopp, J. Fisher, S. Mason, S. McClain, N. M. Sheekh, R. Moss, R. M. Parks, and C. Braneon. Compound risks and complex emergencies require new approaches to preparedness. *Proceedings of the National Academy of Sciences*, 118(19):e2106795118, 2021.
- [21] Francisco P. Santos, Jorge M. Pacheco, Francisco C. Santos, et al. Dynamics of informal risk sharing in collective index insurance. *Nature Sustainability*, 4:426–432, 2021.
- [22] Simon A. Levin, John M. Anderies, W. Neil Adger, et al. Governance in the face of extreme events: Lessons from evolutionary processes for structuring interventions, and the need to go beyond. *Ecosystems*, 25:697–711, 2022.
- [23] Jiafeng Xiao, Linjie Liu, Xiaojie Chen, and Attila Szolnoki. Evolution of cooperation driven by sampling reward. *Journal of Physics: Complexity*, 4(4):045003, oct 2023.

- [24] Antonio Alfonso, Pablo Brañas-Garza, Antonio Cabrales, and Angel Sánchez. The complexity of climate change mitigation: an experiment with large groups. *Journal of Physics: Complexity*, 5(1):015007, feb 2024.
- [25] Longmei Shu and Feng Fu. Eco-evolutionary dynamics of bimatrix games. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 478(2267):20220567, 2022.
- [26] Attila Szolnoki and Xiaojie Chen. Environmental feedback drives cooperation in spatial social dilemmas. *Europhysics Letters*, 120(5):58001, feb 2018.
- [27] Xin Wang and Feng Fu. Eco-evolutionary dynamics with environmental feedback: Cooperation in a changing world. *Europhysics Letters*, 132(6):68001, 2020.
- [28] Silvia Muñoz-Álvarez, Carlos Gracia-Lázaro, and Yamir Moreno. Modeling natural resources exploitation in low-information environments. *Journal of Physics: Complexity*, 5(3):035002, jul 2024.
- [29] Yann Robiou du Pont, Mark Dekker, Detlef van Vuuren, et al. Effect of discontinuous fair-share emissions allocations immediately based on equity. *Nature Communications*, 16(8020), 2025. Published: 03 September 2025.
- [30] Luo-Luo Jiang, Yi-Ming Li, Wen-Jing Li, and Attila Szolnoki. Combined effect of incentives and coupling in multigames in two-layer networks. *Journal of Physics: Complexity*, 6(1):015003, jan 2025.
- [31] Laurie Trenary and Timothy DelSole. Advancing interpretability of machine-learning prediction models. *Environmental Data Science*, 1:e14, 2022.
- [32] P. B. Gibson, W. E. Chapman, A. Altinok, et al. Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Communications Earth & Environment*, 2:159, 2021.
- [33] T. Schneider, L. R. Leung, and R. C. J. Wills. Opinion: Optimizing climate models with process knowledge, resolution, and artificial intelligence. *Atmospheric Chemistry and Physics*, 24(12):7041–7062, 2024.
- [34] Tolulope Ale, Nicole-Jeanne Schlegel, and Vandana P. Janeja. Advancing climate model interpretability: Feature attribution for arctic melt anomalies, 2025.
- [35] P.D.L. Ritchie, J.J. Clarke, P.M. Cox, et al. Overshooting tipping point thresholds in a changing climate. *Nature*, 592:517–523, 2021.
- [36] Te Wu, Feng Fu, Puxuan Dou, and Long Wang. Social influence promotes cooperation in the public goods game. *Physica A: Statistical Mechanics and its Applications*, 413:86–93, 2014.

- [37] Council on Foreign Relations. Funding the united nations: How much does the u.s. pay?  
[https://www.cfr.org/article/  
funding-united-nations-what-impact-do-us-contributions-have-un-agencies-and-programs](https://www.cfr.org/article/funding-united-nations-what-impact-do-us-contributions-have-un-agencies-and-programs),  
2025. Last updated: February 28, 2025; Accessed: 2025-08-14.
- [38] Rachel Pittman and Elizabeth Métraux. Don't believe the disinformation: the un makes  
america stronger. *SDG Action*, September 2024. Accessed: 2025-08-11.
- [39] Better World Campaign. How the un advances u.s. economic interests.  
[https://betterworldcampaign.org/resources/briefing-book-2022/  
united-nations-united-states-economic-interests](https://betterworldcampaign.org/resources/briefing-book-2022/united-nations-united-states-economic-interests), 2025. Accessed: 2025-08-10.
- [40] Takeshi Kuramochi, Swithin Liu, Niklas Höhne, Sybrig Smit, Maria Jose de Villafranca Casas,  
Frederic Hans, Leonardo Nascimento, Paola Tanguy, Angel Hsu, Amy Weinfurter, et al.  
Global, climate action from cities, regions and businesses: Impact of individual actors and  
cooperative initiatives on global and national emissions. 2019.
- [41] Lutz Weischer, Jennifer Morgan, and Milap Patel. Climate clubs: Can small groups of  
countries make a big difference in addressing climate change? *Review of European Community  
& International Environmental Law*, 21(3):177–192, 2012.
- [42] Guocheng Wang, Qi Su, Long Wang, and Joshua B Plotkin. The evolution of social behaviors  
and risk preferences in settings with uncertainty. *Proceedings of the National Academy of  
Sciences*, 121(30):e2406993121, 2024.
- [43] Jing Wang, Feng Fu, and Long Wang. Effects of heterogeneous wealth distribution on public  
cooperation with collective risk. *Physical Review E—Statistical, Nonlinear, and Soft Matter  
Physics*, 82(1):016102, 2010.
- [44] Feng Fu, Martin A Nowak, Nicholas A Christakis, and James H Fowler. The evolution of  
homophily. *Scientific reports*, 2(1):845, 2012.
- [45] Jing Wang, Feng Fu, Te Wu, and Long Wang. Emergence of social cooperation in threshold  
public goods games with collective risk. *Physical Review E—Statistical, Nonlinear, and Soft  
Matter Physics*, 80(1):016101, 2009.