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The role of scale in public goods problems: from pandemics to climate change

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CENTRAL QUESTION

How do system scales shape cooperation in social-ecological public goods problems?

ANSWER

We introduce a framework that captures how three system scales determine regimes of containment, mitigation, and failure to control in social-ecological public goods problems.

FIELD MAP COORDINATES

Emergence; Transformation; Scaling; Space and connectivity.

Abstract

Climate change is a global emergency, as was the COVID-19 pandemic. But our collective response to COVID-19 was much stronger than our response to climate change, to date. Why is that the case? We hypothesize that one reason for the contrasting response in these two systems is their differing scales: not just spatial localization and temporal scale but also personal efficacy, which quantifies how much an intervention directly benefits the individual who adopts it. We introduce a framework that captures regimes of containment, mitigation, and failure to control in social-ecological public goods problems. As parameters governing these three scales are varied, it is possible to shift from a COVID-like system to a climate-like system. The framework replicates both inaction in the case of climate change mitigation, as well as the faster response that we exhibited to COVID-19. The model also exhibits abrupt transitions between regimes and oscillatory dynamics. Our cross-system comparison also suggests actionable ways that cooperation can be improved in large-scale public goods problems, like climate change. More broadly, we argue that considering scale and incorporating human-environment feedbacks are not just interesting special cases within non-cooperative game theory, but rather should be the starting point for the study of altruism and human cooperation.

Introduction

Background

The Intergovernmental Panel for Climate Change (IPCC) called for rapid, unprecedented social change to address the climate emergency [1, 2]. However, progress has been inadequate, despite the risk to lives and economies. In contrast, the COVID-19 pandemic–also a global emergency–stimulated rapid, unprecedented social change in a very short period of time [3–5], even to the extent of reducing global greenhouse gas (GHG) emissions by 14% during shutdowns [6]. This difference in humanity's collective response calls for an explanation [7].

To address this, we present a model that treats climate change and infectious diseases as public goods problems, where everyone in a population benefits from a good that must be maintained by voluntary contributions from individual members. Specifically, both a stable climate and a disease-free state are 'nonexcludable' (everyone benefits from a stable climate or a disease-free state) and 'nonrivalrous' (one person benefiting from a stable climate or the absence of disease does not prevent someone else from also benefiting) [8, 9]. Hence, a stable climate and a disease-free state are public goods. We note that our definition of non-excludability does not imply that all individuals benefit equally. In real-world public goods problems, benefits may be heterogeneous across groups or individuals depending on geography and socio-economic status [10].

In the case of climate change, some mitigation measures (actions taken to reduce a shared threat, such as greenhouse gas emissions or the spread of a pathogen) require individuals to adopt behavior with a real or perceived cost, such as in-

stalling photovoltaic panels on their roof, or walking instead of driving a car [1, 11]. However, climate change mitigation benefits everyone (not just the mitigator) and hence there is a temptation to 'free-ride' by enjoying a stable climate without adopting costly mitigation measures [12–14]. Similarly, herd immunity against an infectious disease benefits everyone, but the reluctance of some individuals to follow public health measures that involve a real or perceived cost (such as mask use or correct use of antibiotics) can lead to resurgence of the infection, thus harming everyone [9, 15–17]. Even though mitigating climate change or an epidemic is best for the group as a whole, non-cooperating might be beneficial at the individual level, so that free-riding harms the public good [18, 19]. Other examples of public goods problems include air quality, water quality, and biodiversity [20]. Everyone benefits from clean air or water, but individuals and industries may pollute without bearing the full cost of the negative impacts [21].

However, other factors can help prevent free-riding and change the game from a Prisoner's Dilemma to a Coordination game, where coordination can allow all players to choose mitigation. This can occur if a penalty is applied to non-mitigation, such as through injunctive social norms [22] or other forms of punishment [23], if decisions occur across multiple hierarchical levels [24] or can unfold through time instead of being instantaneous [23], or if the players think that a dangerous tipping point might occur [25], among other possible mechanisms.

The role of scales

While both climate change and infectious disease control are public goods problems, they are dissimilar in many respects, such as spatial localization. The greenhouse effect involves a well-mixed system (the atmosphere) where emissions from a single tailpipe are dispersed planet-wide after a relatively short period of time, whereas diseases transmitted from person to person spread locally. Although infectious diseases can become globally disseminated, they are not global scale in the same sense as climate change, because they can only spread through local (person-to-person) transmission. An epidemic begins when infection control in the initial stages are a failure, due either to properties of the pathogen, lack of knowledge, or lack of adherence to control measures (the latter of which is our particular focus). If the contacts of Patient Zero act quickly to contain an outbreak, then the epidemic is prevented and the larger population is spared costly mitigation measures. Action by a few individuals can thus prevent exponentially higher morbidity and mortality, and the requirement to adopt costly measures, for those further down the transmission chain. However, if some contacts fail to act and become infected, they may in turn pass the infection to their own set of contacts. As a result, the infection percolates through the entire population and eventually jumps to other populations. This effect has been termed the 'race to trace' in the context of ring vaccination for smallpox [26]. In contrast to the smallpox endgame, we lost the 'race to trace' during COVID-19 due to behavioral and pathogen features, causing us to resort to mass mitigation.

Climate change and infectious diseases also have very different temporal scales. Epidemics caused by acute respiratory viruses pass through a population in a matter of weeks [27, 28], while the impacts of greenhouse gas emissions are manifested over generations [29–32]. Contending with the human tendency to discount outcomes far in the future is a continuing challenge for climate change mitigation, especially given that the decay rate of greenhouse gases is so much slower than the decay rate of a viral infection in a population.

Finally, there is a difference in the personal efficacy of climate change mitigation versus infectious disease control. If a single individual chooses to adopt a climate mitigation measure, the direct benefit to the individual of the resulting reduction in GHG emissions is extremely small and close to zero, thus the personal efficacy–a measure of direct individual benefit–is low. However, an individual adopting a pandemic mitigation measure receives a relatively larger direct benefit through protection from infection, since the personal (clinical) efficacy of masks and vaccines are significantly higher. The differing personal efficacy between climate change mitigation and pandemic mitigation may have implications for which interventions are adopted.

In the same vein, it is worth pointing out that in both systems, the benefit of the mitigator's behavior might be different for the mitigator and the others in the population, according to environmental, health and economic vulnerability. In the climate case, individuals in low-income countries are more impacted by climate change, and thus more benefited by climate change mitigation. In the disease case, an intervention faces a double barrier in order to protect others in the population: it has to be effective both in protecting the mitigator, and also protective in terms of the mitigator not passing on the infection to their contacts. For instance, some vaccines prevent disease in the vaccinated individual but do not block transmission, whereas masking protects the masker and also prevents onward transmission. However, a masker who gets infected might reduce their morbidity while also passing on the virus to a more vulnerable contact [33].

Scale also plays an essential role in many other ecological systems [34]. Mechanisms may operate at very different scales from the patterns they generate. Dynamics at smaller ecological scales may appear highly stochastic, but this can average out to coherent patterns at larger spatial scales [35]. In a similar vein, mechanisms that govern interactions at smaller scales may create emergent patterns at the larger scale of the population ensemble that are difficult or impossible to infer just by knowing the mechanisms [36], such as occurs in animal behaviour [37]. The property of emergence suggests that human behaviour (whether individual or institutional) in ecological and social-ecological systems may not always generate the appropriate response at the appropriate scale [38–40]. We will also observe this effect in the model studied in this paper. Here, using COVID-19 and climate change as motivating examples, we address the central question: 'How do spatial localization, temporal scale, and personal efficacy shape cooperation in coupled social-ecological public goods problems?' We develop a general conceptual and modeling framework showing how these three scales help explain differences among systems, with specific reference to population uptake of mitigation measures against infectious diseases and climate change, and we suggest pathways for improving coop-

eration. Comparing pandemic and climate systems can help address why mitigating the pandemic was partly successful even if the race to trace was lost, whereas mitigating climate change remains a challenge [1, 2, 41–43].

Results

Theoretical Framework

Although both climate change and pandemics are comprised of multiple and very different systems, by 'climate change' we mean a rise in the mean global atmospheric temperature anomaly through anthropogenic release of greenhouse gases, and by 'COVID-19' we mean the seeding of an acute respiratory virus transmitted from person to person in a fully susceptible population, such as for COVID-19 or pandemic influenza, for instance. We hypothesize that variation across three basic scales explains some of the differences in population responses to COVID-19 versus the climate crisis (Figure 1).

- Spatial localization: How widely is a change in individual behavior felt in the natural system? How widely do changes in the natural system impact individuals?
- Temporal scale: How long does it take for individual behavior change to be felt in the natural system? How quickly do changes in the natural system impact individuals? In other words, how long do populations wait to experience the feedback of their collective decisions?
- Personal efficacy: How much direct benefit accrues to the individual adopting mitigation measures?

Our approach is to develop a network-based framework to help us understand how individual behavior in public goods problems depend on these three scales. We test these hypotheses *in silico* [44] through a simplified network consisting of nodes and links. We begin by noting that our approach has limitations. Our model does not analyze the problem at the level of specific social, psychological, and institutional factors (such as trust in institutions and government mandates) known to play a role in these systems and which also determine population responses to COVID-19 and climate change. Integrating these factors into the framework and exploring how they relate to explanations at the level of our three scales is beyond the scope of our paper. In the Discussion, however, we contextualize our framework in the literature on these factors, and suggest ways in which these two different explanatory levels complement one another. Because the framework is more general than either motivating example, we begin with two neutral model archetypes: 'local, fast, self-effective' (LOFASE) and 'slow, non-protective, global' (SNOGLOW). To retain the connection to our motivating question while acknowledging the use of a simplified model, we map these archetypes onto our two model systems, and refer to them from here on as 'COVID-like' and 'climate-like', respectively. These are meant to represent idealized systems, as opposed to being highly realistic descriptors of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) dynamics, or the global temperature anomaly caused by greenhouse gas emissions.

We consider a small-world network of N individuals (nodes), where individuals have an average of Q neighbors (links). We use Q to represent spatial localization: when Q is small relative to N, interactions and their consequences are localized, whereas when $Q \approx N - 1$ they are not. Individuals choose whether or not to adopt mitigation behavior. This behavior impacts the abundance of a natural agent that spreads through network links. A mitigator takes steps to reduce the prevalence of the natural agent, whereas a non-mitigator does not take those steps. This binary classification is a simplifying assumption, since in reality individuals can adopt mitigation measures to varying degrees. The natural agent decays at some rate per unit time (δ). Individuals decide whether to adopt mitigation measures based on a utility function that is determined, in part, by the personal efficacy (ε), representing how effective the behavior is in directly protecting the individual. Other parameters also play a role: the rate of spread of the natural agent through links is governed by transmission parameter (R). Adopting control measures imposes a cost on the mitigator (c_M), and a person impacted by infection or climate change also suffers a cost (c_I). There is an average duration of time that individuals spend in the impacted state (D). Nodes that are exposed to the natural agent suffer impact to their well-being with a specified probability (β). The model is specified in Section , and details of the simulation are in the Supplementary Appendix.

The natural agent has a different interpretation in each system. In the climate-like system it represents atmospheric greenhouse gases (GHG), and its presence at a node means that the individual is exposed to elevated GHG concentrations. In the COVID-like system it represents a communicable pathogen, and its presence at a node means that the individual carries that pathogen. The processes acting on the natural agent also have a different interpretation in each system. Generation corresponds to GHG emissions in the climate-like system, and to case importation in the COVID-like system. Transmission corresponds to atmospheric mixing and to person-to-person transmission, respectively. Decay corresponds to carbon sequestration or absorption and to recovery from infection, respectively.

Each of the three scales–spatial localization, time and personal efficacy–is governed by a model parameter: neighborhood size Q (for spatial localization), decay rate δ (for time) and personal efficacy ε. These parameters differ by orders of magnitude between the two systems. Greenhouse gas emissions caused by a single person spread globally, so spatial localization is absent and the relevant network is fully connected, where every person is connected to every other person ($Q = N - 1$). In contrast, diseases that are transmitted from person to person spread to a relatively small number of neighbors ($Q \ll N$). For climate change, the decay rate δ is low, since greenhouse gases persist for a long time in the atmosphere, but for acute respiratory infections that resolve in days or weeks, δ is high. Finally, the incremental benefit to a single individual mitigator due to reducing GHG emissions is very small because the resulting incremental change in worldwide GHG emissions is tiny, hence $\varepsilon \approx \frac{1}{N} \approx 0$. Infectious disease interventions can provide a significant benefit to the individual mitigator who adopts them, regardless of whether they are effective in protecting others or how large the population size is, hence $0 \ll \varepsilon < 1$.

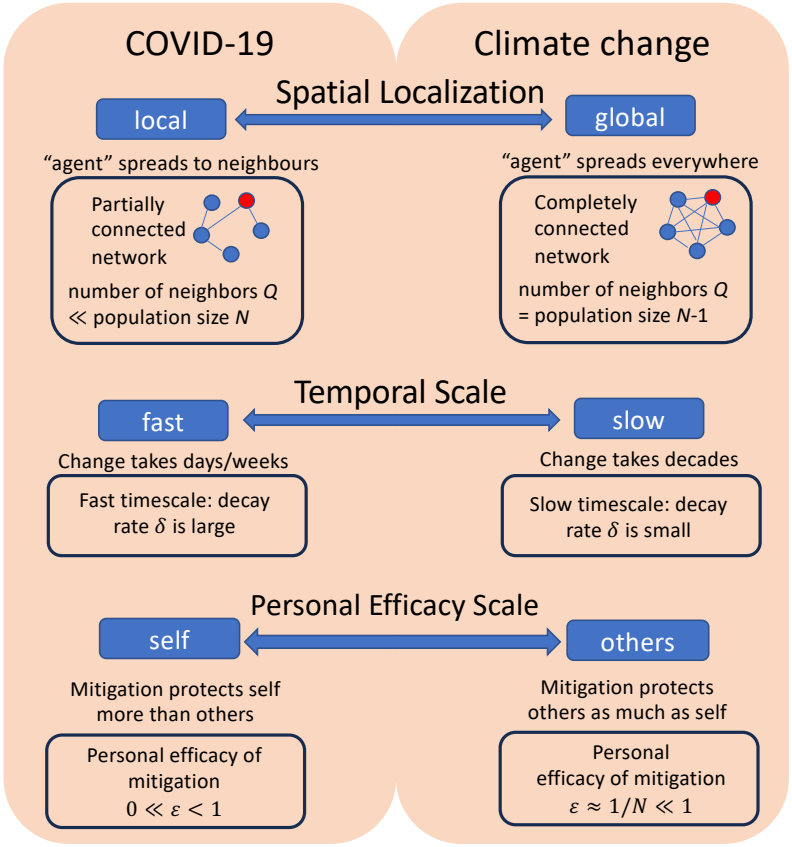


Figure 1: Schematic representation of the spatial localization, temporal and personal efficacy scales in COVID-19 and climate change. The two systems differ significantly with respect to each of these scales.

Model specification

Each node i has a behavioral state $B_i \in \{M, N\}$ (mitigator or non-mitigator), a state of well-being $H_i \in \{W, I\}$ (well or impacted), and an agent status $A_i \in \{1, 0\}$ (natural agent present or absent). The network and the simulation are described in the Supplementary Appendix.

Behavioral transitions

The utility for node i by choosing non-mitigating behavior is given by

$$e_{i,N} = -p_i^N c_I D \tag{1}$$

whereas the utility for mitigating is

$$e_{i,M} = -p_i^M c_I D - c_M \tag{2}$$

where c_M is the cost of being a mitigator, c_I is the cost of being impacted, D is the duration of the impact, p_i^M is the probability of being impacted if node i is a mitigator, and p_i^N is the probability of being impacted if node i is a non-mitigator. The probabilities p_i^M and p_i^N are given by:

$$p_i^M = \beta(1-\varepsilon)(1 - e^{-RA_i^{risk}}) \tag{3}$$

$$p_i^N = \beta(1 - e^{-RA_i^{risk}}) \tag{4}$$

where $0 < \beta < 1$ controls the probability of impact (analogous to morbidity risk), $0 \leq \varepsilon \leq 1$ is the personal efficacy of mitigation, R controls how rapidly the natural agent is transmitted through the network, and $A_i^{risk} = \frac{1}{k_i}\sum_{j\in\mathcal{N}_i} A_j$ represents the proportion of the k_i neighbours of node i (the set $\mathcal{N}_i$) that carry the natural agent (agent status ‘1’). This represents the local risk to node i. Note how ε reduces the risk of being impacted due to local prevalence A_i^{risk}, but mitigators must also pay a cost c_M for that protection.

In each timestep, with a probability $0 < \sigma \leq 1$, a node decides whether to change its behavior. A node that is currently not mitigating will switch to mitigation if

$$e_{i,M} \geq e_{i,N}$$

while a node that is mitigating will switch to non-mitigation if

$$e_{i,N} \geq e_{i,M}$$

Physical transitions

If the natural agent is present at a node, it decays with probability δ per timestep, changing the node’s agent status from ‘1’ to ‘0’. In each timestep, a non-mitigator that currently has agent status ‘0’ changes to agent status ‘1’ with a generation probability p_{gen}, indicating the natural agent is now present. This corresponds to individual behavior that is responsible for greenhouse gas emissions in the climate-like system, or to case importation in the COVID-like system. The natural agent can also be transmitted to other nodes, depending on whether participating nodes are mitigators, who attempt to protect

themselves from spread according to the personal efficacy ε. In particular, if a node's current status is '0', it will receive the natural agent from its neighbours with probabilities

$$p_i^{inf,M} = (1-\varepsilon)(1-e^{-RA_i^{risk}}) \tag{5}$$

if they are a mitigator, and

$$p_i^{inf,N} = (1-e^{-RA_i^{risk}}) \tag{6}$$

if they are a non-mitigator. We note that agent status is imperfectly analogous to the infection state in compartmental epidemic models [45], whereas the impacted state corresponds to a state of disease/morbidity caused by an infection.

Well-being transitions

A currently 'well' node with the natural agent (new or existing) becomes impacted with probability β, and an impacted node recovers with probability $1/D$ per timestep, where D is the average duration in the impacted state.

Decision threshold

Equations 1–4 imply a simple threshold for the behavioral decision. A node prefers mitigation ($e_{i,M} \geq e_{i,N}$) when

$$\beta\varepsilon c_I D(1-e^{-RA_i^{risk}}) \geq c_M, \tag{7}$$

that is, when the expected reduction in the cost of being impacted is at least the cost of mitigation. Because the left-hand side increases with the local risk, a node mitigates when A_i^{risk} reaches the critical value

$$A^* = -\frac{1}{R}\ln\left(1-\frac{c_M}{\beta\varepsilon c_I D}\right), \tag{8}$$

and if $c_M > \beta\varepsilon c_I D(1-e^{-R})$, mitigation never pays, whatever the local risk. A node with k_i neighbors can only have $A_i^{risk} \in \{0, 1/k_i, 2/k_i, \ldots, 1\}$, so the number of neighbors carrying the natural agent that is needed to trigger mitigation is $\lceil k_i A^* \rceil$. For example, with the COVID-like values in Table 1 of the Supplementary Appendix ($\beta = 0.2$, $\varepsilon = 0.95$, $c_I = 1000$, $D = 5$, $R = 5$), a single neighbor carrying the natural agent, out of four, triggers mitigation whenever $c_M \leq 678$, which quantifies the sense in which one affected neighbor is a 'clear and present threat'. The same expression accounts for the stepwise transitions as the cost of mitigation increases, which occur near $c_M = 600$, 678, 770 and 872, where a node with five, four, three or two neighbors, respectively, first needs more than one affected neighbor before it mitigates; for the effect of Q, which lowers the risk contributed by each neighbor ($1/k_i$); and for the effect of ε, below which mitigation never pays.

Containment, mitigation and non-control

This framework captures regimes of containment, mitigation, and non-control, for both study systems. For the COVID-like system, with a relatively low neighborhood size Q, fast decay rate δ, and high personal efficacy ε, the mitigation regime is easier to obtain, and it occurs even when the cost of mitigation (c_M) is relatively high (Figure 2, top). However, in the case of the climate-like system, achieving the mitigation regime is more challenging. The population is completely connected ($Q \approx N-1$) and hence spatial localization does not occur–the population is homogeneously mixing. Personal efficacy ε is likewise very small, so the number of individuals who choose not to mitigate grows rapidly. Climate change can only be prevented if the cost of mitigation c_M is very small (Figure 2, bottom); otherwise, the system enters the non-control regime. Should the cost of mitigation become negative, such as when renewable sources of energy cost less than carbon-based sources, then containment is achievable.

Closer study of the framework suggests why these differences occur, and also reveals a third dynamical regime of containment. Consider a hypothetical scenario where a small number of non-mitigators are distributed throughout the population, and they are emitting the natural agent at some rate. How do their neighbors react? In the containment regime, a sufficient proportion of neighbors immediately choose mitigation, thus blocking further spread of the natural agent. The mitigation regime, in contrast, can arise through two distinct mechanisms. In the first (partial adoption), many neighbors choose to mitigate, but some others do not, thus allowing the spread of the natural agent into new areas of the network and causing percolation of both natural agent and partial mitigation throughout the network. In the second (imperfect efficacy), the neighbors do choose to mitigate, but the personal efficacy is not high enough to prevent the natural agent from continuing to spread through them. Finally, in the third non-control regime, almost no neighbors choose mitigation, and the natural agent spreads widely, impacting all individuals in the network.

We define these regimes operationally, using the percentage of nodes that are mitigators and the percentage of nodes at which the natural agent is present, each measured at the end of a simulation (in Figures 2–4, as the average over the final 70% of time steps). A simulation is in the mitigation regime if more than 30% of nodes are mitigators; in the containment regime if at most 30% of nodes are mitigators and the natural agent is present at no more than 30% of nodes; and in the non-control regime if at most 30% of nodes are mitigators and the natural agent is present at more than 30% of nodes. These definitions might differ from those used in public health practice, because the natural history of the system depends so strongly on Q, δ and ε, but they qualitatively capture the differences between these regimes. Every simulation falls into exactly one of the three regimes by construction; the substantive results are where the boundaries between the regimes lie in parameter space, and how they move as Q, δ and ε vary (Figure 4 and Supplementary Figures 1–10).

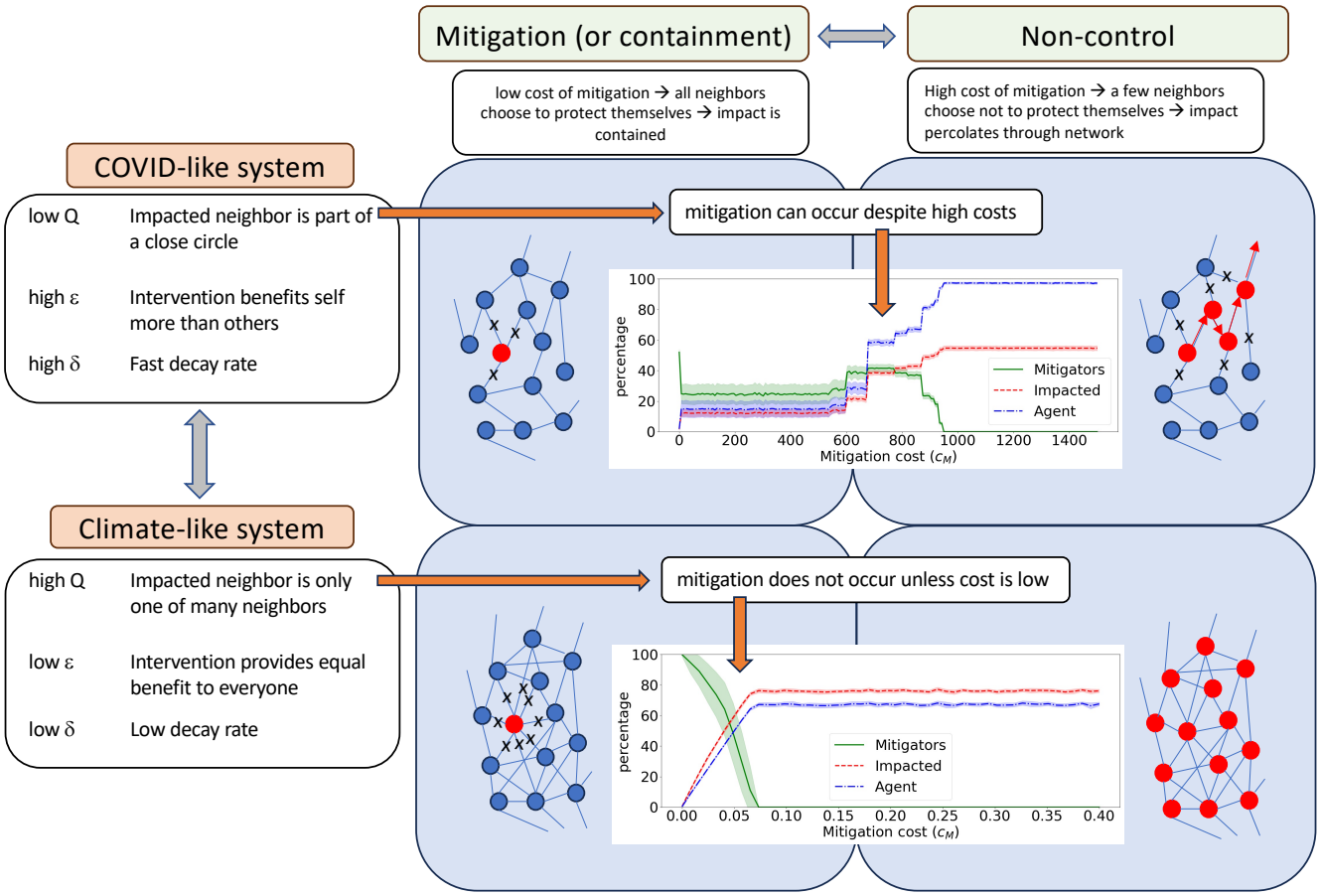


Figure 2: Containment, mitigation, and non-control regimes for COVID-like and climate-like systems. The cost of mitigation has to be significantly lower for the climate change system, in order to facilitate the uptake of mitigating behavior. Parameters are in the Supplementary Appendix: Table 1. Agent denotes the percentage of nodes at which the natural agent is present. Each point on a curve is one simulation; curves show the mean over the final 70% of time steps, and shaded regions denote one standard deviation over the same window.

This intuition is borne out in simulation results of the agent-based network model. In the case of the COVID-like system, when mitigation measures are not too costly, the neighbors of any initial non-mitigator nodes are more likely to adopt mitigation, since that single non-mitigator neighbor is a clear and present threat representing a considerable share of a node's total number of contacts, and the personal efficacy is high enough to motivate a choice to mitigate. Thus, all neighbors of the non-mitigator adopt mitigation, and the natural agent is contained (Figure 3, top left). The prevalence of the natural agent is nevertheless nonzero in this regime because of case importation: the natural agent can still be introduced into the network at non-mitigator nodes, but the population responds by preventing its further transmission through containment. As the natural agent is repeatedly reintroduced, a persistent nonzero level of the natural agent remains in the population at all times, without widespread transmission. Simulations in this regime show that the population responds quickly to surges in the natural agent prevalence, acting to contain the natural agent and causing it to decline once again. The result is cycles of epidemic outbreaks [46] and behavioral responses [47], similar to those seen in many infectious disease systems (Figure 3, top left). This regime covers a broad portion of the c_M parameter space, on account of the strong negative feedback loop that containment represents. However, if the mitigation cost is somewhat larger, a few neighbors will choose not to mitigate. This allows percolation of the natural agent through the network, and a suboptimal outcome of both higher levels of natural agent and higher levels of mitigation (Figure 3, top middle). Thus, increasing the mitigation cost can increase the number of mitigators. This occurs because the rising cost makes the rings of mitigators around a non-mitigator 'leaky': the natural agent can occasionally leak through a ring, spurring another round of containment in the adjacent part of the network. The population loses the 'race to trace' [26], and the paradoxical (and suboptimal) outcome is that both mitigation behavior and natural agent prevalence are more widespread. The transition between these two dynamical regimes is abrupt, on account of the fact that the negative feedback loop of containment can be overcome by the positive feedback loop of natural agent propagation, once the cost of mitigation becomes too high. In fact, the model simulation shows several such transitions as c_M is increased, reflecting the additional role played by the network

geometry: a node's local risk can only take a discrete set of values determined by its number of neighbors, so the cost at which a node adopts mitigation changes in steps (Figure 3, middle). If the mitigation cost is very large, no neighbors will choose to mitigate, and the non-control regime is obtained, with few mitigators and a high number of impacted nodes (Figure 3, top right).

For the climate-like system, a containment regime does not occur at our baseline parameter values, although a mitigation regime is possible at a sufficiently low cost of mitigation (Figure 3, middle). There is a very small regime of cycles in behavior, although the temporal evolution of the natural agent is too slow for the cycles to be very pronounced in the natural agent prevalence time series (Figure 3, bottom left). For higher values of the mitigation cost, mitigation fails altogether and the natural agent spreads without hindrance (Figure 3, bottom right). In both systems, the success of mitigation depends on the time scale of mitigating behavior being at least as fast as the timescale of natural agent spread. When the natural agent spreads as fast as mitigating behavior evolves, a tight feedback loop is possible. If the spread of the natural agent is much slower than the uptake of mitigation, then behavior always adapts quickly enough to keep the natural agent under control. But slow behavioral change allows the natural agent to spread faster than the population can adapt its behavior.

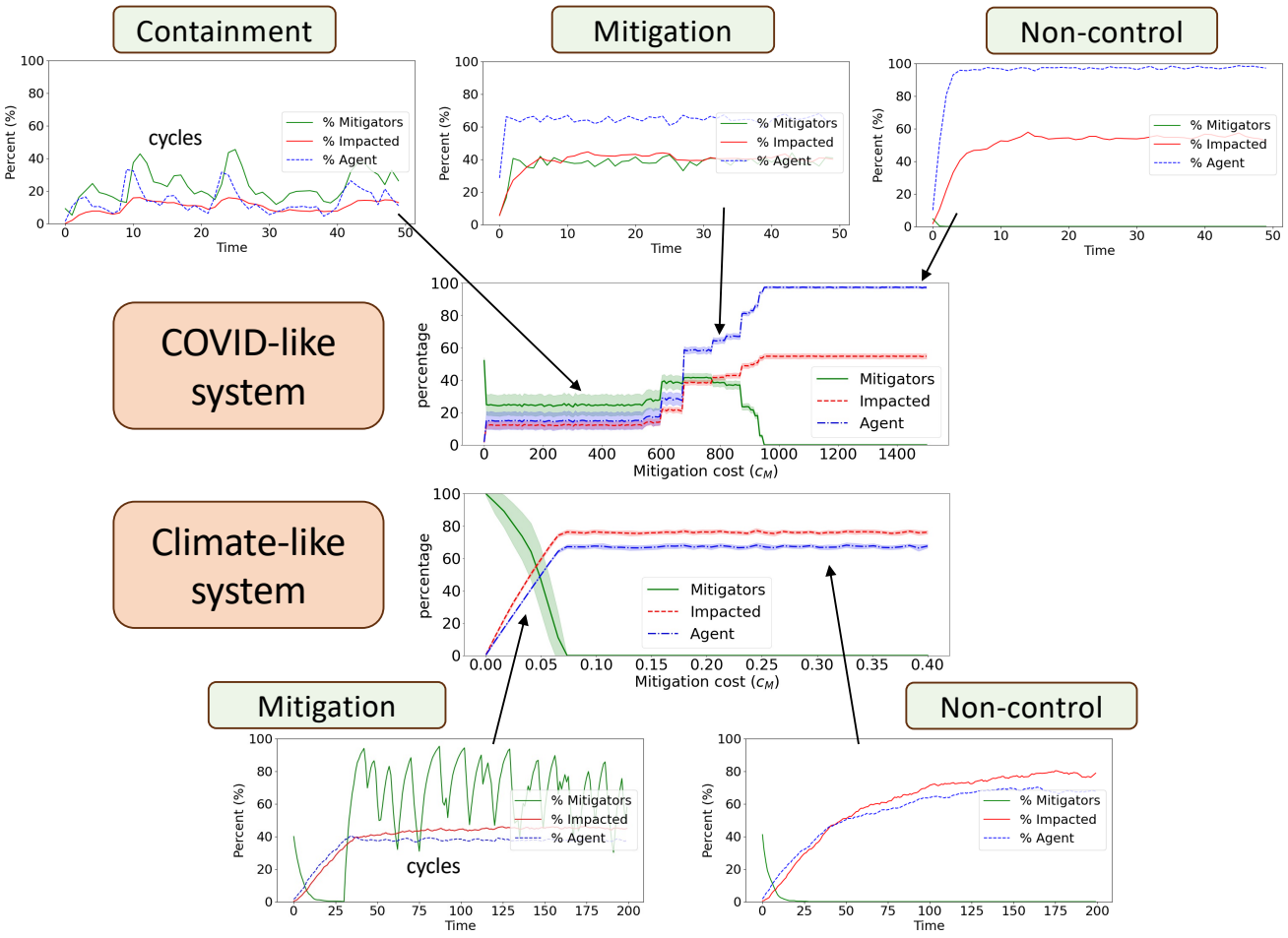


Figure 3: Temporal dynamics. The COVID-like system exhibits a broad regime of containment, and cycles in both behavior and natural agent prevalence. The climate-like system only allows for a narrow regime of mitigation where pronounced cycles are possible for behavior but not natural agent prevalence. Parameters are in the Supplementary Appendix: Table 1. Agent denotes the percentage of nodes at which the natural agent is present. Each point on a curve is one simulation; curves show the mean over the final 70% of time steps, and shaded regions denote one standard deviation over the same window.

It is possible to move the system between regimes by varying only the three scaling parameters for the neighborhood size Q, decay rate δ, and personal efficacy ε, while all other parameters are held constant (Figure 4). As the neighborhood size increases, the system moves from the containment regime in a localized network to the mitigation regime (Figure 4a). There are two competing effects on the fraction of mitigators. First, because each non-mitigator has more neighbors, more individuals need to participate to maintain the protective ring around it, and thus, if mitigation is favorable, more individuals choose mitigation. Second, as the neighborhood size increases, the neighbors of non-mitigators are less incentivized to adopt mitigation on account of the diminishing direct impact to them individually. If this incentive is suf-

ficiently weakened, the natural agent can leak through the imperfect rings of protection, stimulating a further round of partial containment in the adjacent part of the network. This yields the mitigation regime, where there is some control and a high prevalence of mitigators. If mitigation is sufficiently unattractive, the non-control regime is obtained instead, where the natural agent spreads widely and there are few mitigators; this does not occur over the range of Q in Figure 4a, but it does occur when mitigation is less attractive, such as at lower values of R, c_I, β or D (Supplementary Figure 2). When the personal efficacy (ε) is very high, containment is possible on account of the intervention being attractive to individuals, and effective as a means to prevent natural agent spread (Figure 4b). However, for lower values of ε representing an imperfect intervention, the natural agent is able to percolate through imperfect rings of mitigator neighbors. As a result, both mitigation behavior and natural agent prevalence are higher [48]. However, when ε is very small, mitigation becomes too unattractive to justify the cost, and the population abandons it altogether. Finally, at high values of the decay rate, it is relatively easy to contain the natural agent, but at lower values of the decay rate, the natural agent persists for long periods of time and this makes it difficult to contain, necessitating more widespread mitigation (Figure 4c). Transitions in the timescale parameter δ result in a more gradual switch between the systems. In the case of climate change, these regimes correspond to the expected initial failure to take up climate change mitigation on account of low ε, followed by partial adoption of mitigation as the impacts grow over time (Figure 4b, $\varepsilon \approx 0.05$). If the decay rate δ is small, eventually there are enough greenhouse gases to force more of the population to choose mitigation, although by this time the natural agent and its impacts are already widespread (Figure 4c, $\delta \approx 0.01$).

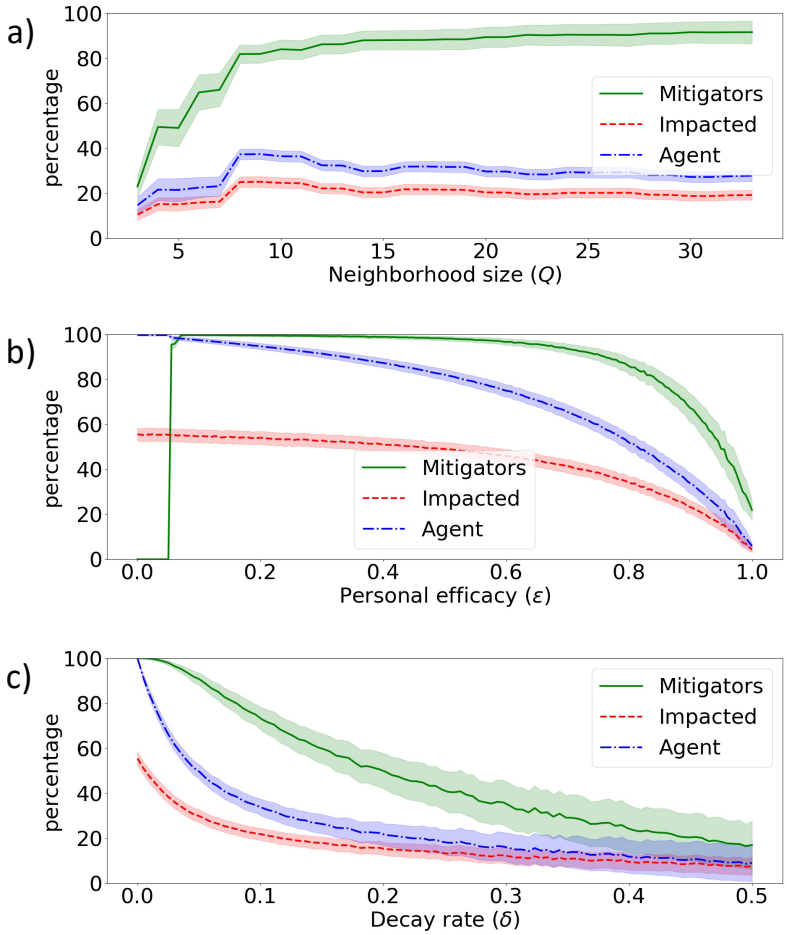


Figure 4: Effect of varying the three primary scaling parameters on dynamical regime, for (a) neighborhood size Q, (b) personal efficacy ε, and (c) decay rate δ. In each panel only the indicated parameter is varied, and all other parameters are held constant at $Q = 5$, $\varepsilon = 0.95$, $\delta = 0.2$, $R = 5$, $D = 5$, $\sigma = 1$, $c_I = 1000$, $\beta = 0.2$, $p_{gen} = 0.02$ and $N = 300$, with $c_M = 450$ in panel (a) and $c_M = 50$ in panels (b) and (c). As Q increases, the regime changes from containment to mitigation (a); as ε increases, it changes from non-control to mitigation to containment (b); and as δ increases, it changes from mitigation to containment (c). The step structure of subpanel (a) arises because the network generator in the NetworkX package gives a mean degree of $2\lfloor Q/2 \rfloor$, so that an odd value of Q produces the same network as $Q - 1$ (see Supplementary Appendix). Agent denotes the percentage of nodes at which the natural agent is present. Each point on a curve is one simulation; curves show the mean over the final 70% of time steps, and shaded regions denote one standard deviation over the same window.

As a sensitivity analysis, we repeated these sweeps of ε, Q and δ at four values of each of the parameters R, c_I, β and D, using 50 independent runs for each point, each with its own network realization and initial conditions, so that the results are not artifacts of a particular stochastic realization (Supplementary Figures 1–3). Varying ε produces all three regimes in most cases, in the order non-control, mitigation and containment as ε increases. Varying δ produces mitigation at low δ and containment at high δ in half of the cases, while in cases where mitigation is less attractive the system ends in non-control at high δ or remains in non-control throughout; with a low rate of spread ($R = 1$), the system passes from mitigation through non-control to containment as δ increases. Varying Q usually produces containment at small Q, followed by mitigation at larger Q when mitigation is attractive or by non-control when it is not, such as at low values of R, c_I, β or D; at $R = 2$, the system passes from containment through non-control to mitigation as Q increases. We also repeated these sweeps on random regular networks (Supplementary Figures 4–6) and scale-free networks (Supplementary Figures 7–9), and obtained qualitatively similar results.

For the climate-like system, the neighborhood size and the personal efficacy both follow from the population size ($Q \approx N - 1$ and $\varepsilon \approx 1/N$), and so they move together when N is large. However, they are conceptually independent: Q describes how localized the spread of the natural agent is, whereas ε describes how well mitigation protects the mitigator. To separate their effects, we varied Q and ε jointly, holding the other parameters at the values used in Figure 4a (Supplementary Figure 10). The containment regime occupies a small region of this plane at small Q and high ε, which corresponds to the COVID-like system. The non-control regime occupies the whole region of low ε, at all values of Q, and this region includes the climate-like corner of large Q and low ε. The boundary between the mitigation and non-control regimes lies at $\varepsilon \approx 0.45$ and does not depend on Q, because below $\varepsilon = c_M/(\beta c_I D(1 - e^{-R})) \approx 0.45$ mitigation does not pay even for an individual whose neighbors all carry the natural agent (Equation 7). The rest of the plane, including small Q with intermediate ε and large Q with high ε, is in the mitigation regime and corresponds to neither motivating system. At these parameter values, therefore, low personal efficacy is sufficient by itself to prevent mitigation, whereas containment additionally requires a small neighborhood size. This qualifies the role of spatial localization in our framework: at these parameter values, spatial localization determines whether the natural agent can be contained, but personal efficacy determines whether it can be mitigated at all, so the contrast between the COVID-like and climate-like systems reflects both scales acting together rather than spatial localization alone.

Finally, we also tested the sweeps in Figure 4 for robustness to the initial fractions of mitigators and of nodes carrying the natural agent, to the population size N, and to the rewiring probability of the small-world network, which controls its clustering (Supplementary Figures 11–13). We found that these factors did not qualitatively change the results, either. We note that Figures 2–4 each show a single simulation per point, averaged over the final 70% of time steps. Our sensitivity analyses, which use 50 independent realizations per point, give the same regimes as Figure 4, and the system appears to be ergodic, so these time averages are representative of averages over independent realizations.

Discussion

The effects of spatial and temporal scales on ecological systems has long been a topic of study [34]. However, the impact of these scales on public goods problems is less studied [49–52] and comparative analysis of specific system types is rare. Here we proposed an explanation for the widely differing reaction to the emergencies of COVID-19 and climate change, in terms of not only spatial localization and temporal scale, but also personal efficacy, which quantifies the direct benefit of a behavior to the individual adopting it. The concept of personal efficacy emerges naturally once public goods problems are moved into a human-environment framework, where we are forced to consider how actions affect a natural system, which in turn affects the human population again, in a two-way feedback loop [53–57].

Personal efficacy and benefit asymmetry are related but distinct concepts. Personal efficacy ε measures how much mitigation reduces the mitigator's own risk of acquiring the natural agent and being impacted (Equations 3–6). Benefit asymmetry concerns how the benefits of an individual's action are distributed between that individual and others. In our model, the benefit to others depends not only on ε but also on how much natural agent a mitigator prevents from being generated and passed on, and thus on p_{gen}, R, δ and the network structure. The same value of ε could therefore correspond to different degrees of benefit asymmetry under different system conditions. For this reason we treat ε strictly as personal efficacy, and we regard it as only a partial proxy for benefit asymmetry. The distinction parallels the economics of impure public goods, in which a single action jointly produces private and public benefits [58, 59], and the divergence between individual self interest and the population social optimum in vaccination [60].

A further distinction can be drawn between benefit asymmetry and what might be called a control scale: the extent to which one individual's action can measurably influence the collective state. Benefit asymmetry asks who receives the benefits of an action, whereas the control scale asks whether the action makes a detectable difference at all. In a localized network, a single individual accounts for a substantial share of each neighbor's local risk, whereas in a fully connected network of size N their share is of order $1/N$. Individually negligible contributions are central to the literature on rational participation in collective action. A member of a large group can withhold a contribution without noticeably reducing the supply of a public good [61], and the probability that a single vote decides a national election is incrementally tiny [62]. In experimental social dilemmas, perceived efficacy and cooperation are higher in small groups than in large ones, even when members' objective influence is the same [63], and philosophers have debated whether an individual's contribution to a collective harm, such as their emissions, makes any difference [64, 65]. Experiments on collective-risk social dilemmas also show that groups are more likely to avert simulated dangerous

climate change when the risk of loss is high [66]. Our model does not include a separate control scale, because individuals respond only to their own local risk and do not estimate their influence on the population as a whole. Adding one would be a natural extension of our framework.

Our modelling framework is closely tied to questions of altruism and cooperation in human populations. The study of why humans cooperate and how cooperation can be sustained is a question of enduring scholarly interest [67–69]. We think that both system scale and natural system feedbacks are indispensable to the study of human cooperation. With respect to the role of scale, it has been previously noted how humans continue to cooperate in large populations even in one-shot interactions [68, 70], and despite the fact that our cooperative tendencies evolved in small hunter-gatherer groups [51]. Whether human cooperation can be sustained in a globalized society–and for how long–is an existential question that can be answered by explicitly addressing the role of scale. With respect to the role of resource dynamics and natural system feedbacks, we note that most of the theory of cooperation has been developed for fixed payoff matrices where the decisions of players do not impact the payoff they receive [71]. This is a good first approximation. However, most of the things that humans compete for in the real world are of limited availability and can be depleted, which is why they are a source of competition in the first place. Thus, we argue that studying cooperation in coupled human-environment systems [54, 55], and especially the role of scale in these systems [72, 73], is not merely a special case of non-cooperative game theory [74], but rather should be its starting point and primary framework.

Our framework necessarily makes simplifying assumptions that could affect its predictions. For instance, we assume that individuals have perfect knowledge of their impact risk, and that decisions are based solely on parameters such as utilities, mitigation costs and cost of impact. We also intentionally modelled the natural system dynamics in similar ways for COVID-19 and climate change, aside from differences in the parameter values used.

Some of our conclusions depend on this common dynamical structure more than others. The finding that uptake of mitigation is governed by the balance between its cost and the reduction in personal risk (Equations 1–4) follows from the utility function, and does not depend on whether the natural agent is a pathogen or atmospheric carbon. However, containment depends on a natural agent that spreads between discrete nodes and can be blocked by rings of mitigators. This is a natural description of person-to-person transmission, but only an idealized description of atmospheric carbon, which is well mixed and for which warming depends on cumulative emissions [75], whereas the binary agent status of a node cannot accumulate. We therefore regard the contrast between the two systems as qualitative: it shows how Q, δ and ε shape the regimes of a common model, rather than predicting cost thresholds for either real system.

We have referred to the changes between regimes simply as transitions, and to the cycles in Figure 3 as oscillatory dynamics, because abrupt changes do not by themselves establish a tipping point, and oscillations do not by themselves establish a stable limit cycle, for example. The network modelling literature suggests several phenomena that these transitions might represent. Threshold decision rules on random networks can generate global cascades, with a continuous transition at one boundary of the region where cascades occur and a discontinuous transition at the other [76]. Adaptive feedback between node states and network structure can produce oscillations, hysteresis and first-order transitions [77], and on scale-free networks the epidemic threshold can be absent altogether [78]. The threshold-like decision rule in our model and the discrete values taken by local risk are compatible with a cascade mechanism, but identifying which phenomenon operates here would require further evidence, such as tests for hysteresis and alternative attractors or a bifurcation analysis.

The framework provides a high-level 'zoomed-out' perspective intended to generate insights about how the three scales of the environmental system–the decay rate of the natural agent (δ), the personal efficacy of the intervention (ε), and the neighbourhood size through which the effects of the natural agent are felt (Q)–affect human-environment dynamics. This contrasts with the more common approach–from the human side of the human-environment system–that explores the role of factors relating to psychology, altruism, social effects including social learning and norms, institutional arrangements, political authority, governance capacity, and communication dynamics. We did not include these in order to focus on a simple baseline model of the impact of environmental scales on decision-making. Some of these human-side factors find echoes in our framework, while others fall explicitly outside of the framework and would require adapting it.

For example, in a heterogeneous population, different individuals or groups may have different levels of benefit asymmetry. In the case of climate change, those who contribute the most greenhouse gas emissions are typically not the ones who will benefit the most from climate change mitigation. Thus, even within the same population, greenhouse gas (GHG) emitters would have an even lower value for their personal efficacy than those who are vulnerable to climate change. Unless altruism is present, this situation will suppress mitigation [79]. This contrast and its cause of climate inaction has been highlighted in the environmental psychology literature on climate justice [80, 81]. This effect is also present in the case of pandemics but is less strong. Masking provides significant benefits to self, which imposes a clear nonzero minimum for personal efficacy. Moreover, because infection is transmitted from person-to-person, a connected subpopulation (e.g. an urban neighbourhood) with a higher prevalence of vulnerable individuals can generate benefits for itself by masking and thus reducing local transmission of the pathogen. Hence, the benefit asymmetry is more consistent across subpopulations in the case of pandemics. In the language of our framework, because the personal efficacy of mitigation measures are higher for infectious diseases, their adoption is less reliant on altruistic motivations than for climate change mitigation and thus should be less subject to such barriers [82, 83]. Our framework could be expanded to consider the impact of population heterogeneity in vulnerability.

Future work could further expand on benefit asymmetry. Here, we simply equated personal efficacy with clinical

efficacy and changed the interpretation of the parameter. However, perhaps the (clinical) efficacy of an intervention could be re-framed in the context of whether the intervention's uptake relies upon altruistic motives, versus simply relying upon directly personal benefit to the mitigator. Accordingly, future epidemiological studies could estimate not only clinical (personal) efficacy of an intervention, but also the 'social efficacy'–how well an intervention protects others, especially for transmissible conditions like infectious diseases or obesity [84]. Modelling studies could study how decision-making is affected by both types of efficacy according to their benefit asymmetry. This could allow using the framework to understand when and how other-regarding preferences can be a motivator for mitigation, such as when considering the multi-generational impacts of climate change [50, 85], or the desire to protect immediate family and vulnerable members of the community through contact precautions, during the COVID-19 pandemic [86].

Our temporal scale parameter δ concerns the rate of decay of the natural agent and we find that a slow temporal timescale can result in inadequate control efforts (Figure 4c). On the human side, social and psychological factors generate temporal discounting of future outcomes, which has a similarly deleterious impact on health and sustainability outcomes. Acting today for the benefit of future generations can be difficult. We do not assume that individuals look forward in time in our framework, but the framework could be extended to add a fourth scale for temporal discounting. In the same way, our framework focussed on the effect of spatial localization in environmental processes on human-environment dynamics, but the spatial and social scales of human systems are also relevant [87]). If individuals differ along axes of both time and social distance (more socially distinct from oneself [88]), it can be exponentially more challenging to motivate action [89–91]. In ethics and psychology, it has been recognized how many social challenges require acting over large social scales by requiring people to give resources to others who are socially distant, dissimilar, or difficult to see as part of the self [92, 93] and this can prevent altruistic actions [88, 91, 94–97]. In the same vein, game theoretical models on 'viscosity' have identified the role of spatial locality in promoting altruism and cooperation (through providing benefits to likely kin) [98]. Our framework could be extended through a fifth scale for social distance, which would also benefit from the extensive literature on complex network structure [99, 100] and especially the role of social processes on networks [101].

Our framework is a model of individuals and ignores governments and institutions. The importance of interactions between governmental and environmental scales it clear. For example, the lack of institutional arrangements and political authority that can effectively enforce climate change mitigation stems partly from the fact that human political authority is stronger at national and sub-national levels, which are suitable for controlling a locally transmitting infectious disease, but not a globally dispersed greenhouse gas. The concept of scale, and interactions across scales, has previously been studied in the context of environmental governance [102, 103]. Still, until relatively recently, it has been argued that scale-related issues are often overlooked, despite being key in addressing climate adaptation [104]. However, this organizational complexity of human systems has been identified as being crucial for public goods problems (and common pool resource problems, which are a related class of problems) [105]. For instance, better resource management happens under combined community and governmental efforts [106, 107]. In addition to sustainability, common pool resource management focuses on multiple factors, such as government and community interactions along with cultural, economic, and ecological factors, by looking at the interaction between human and environmental systems [108, 109]. In a similar vein, the NIMBY effect (Not In My Back Yard) exemplifies a conflict between global benefits and local costs similar (though not identical) to that of climate change, that could be studied with our framework.

Our framework identified the cost of mitigation as one of the main determinants of mitigating behavior, for both COVID-like and climate-like systems. However, the population may adopt control measures at a higher cost for COVID-like systems than for climate-like systems. This reflects how individuals during the first wave of COVID-19 were willing to adopt not only contact precautions like handwashing, mask wearing and social distancing, but also more costly measures such as school and workplace closures. In contrast, control or even mitigation against climate change requires a very low cost to control or mitigate, on account of the large neighborhood size, slow decay rate, and low personal efficacy. If this low cost can be achieved, then the switch to mitigation behavior is quick. This switch might be accelerated by a change from net costs for renewable energy to net savings relative to carbon-based energy sources, for example [110].

This framework also suggests possible strategies to accelerate the uptake of climate change mitigation. For instance, the framework suggests that framing a problem as local instead of global (smaller Q) could help support uptake. For climate change, this could occur through emphasizing co-benefits of reduced greenhouse gas emissions, such as air pollution reduction [111]. Approaching climate change as a local problem can also leverage faster behavioral change by considering the local and shorter-term impacts (high δ) of extreme weather events like heatwaves, floods, and droughts.

In conclusion, comparing public goods problems with very different spatial localization, temporal scales, and personal efficacy may not only explain differences in population behavior, but also suggest ways in which more sustainable behaviors could be encouraged. If pandemics and climate change exemplify coupled human-environment systems, then a fuller understanding must consider the role of not just social but also environmental scales and processes in population decision-making. Our work contributes to bridging the gap between social science approaches to scales and mathematical modelling of scale effects in human-environment systems.

References

[1] V. Masson-Delmotte et al. "IPCC, 2021: Summary for policymakers. in: Climate change 2021: The physical science basis. contribution of working group i to the sixth assessment report of the intergovernmental panel on climate change" (2021).

[2] T. Kanitkar, A. Mythri, T. Jayaraman. "Equity assessment of global mitigation pathways in the IPCC Sixth Assessment Report". *Climate Policy*, 1–20 (2024).

[3] M. Ciotti et al. “The COVID-19 pandemic”. *Critical reviews in clinical laboratory sciences* 57, 365–388 (2020).

[4] T. Ling et al. “Effects of the coronavirus (COVID-19) pandemic on social behaviours: From a social dilemma perspective”. *Technium Soc. Sci. J.* 7, 312 (2020).

[5] J. Shachat, M. J. Walker, L. Wei. “How the onset of the COVID-19 pandemic impacted pro-social behaviour and individual preferences: Experimental evidence from China”. *Journal of Economic Behavior & Organization* 190, 480–494 (2021).

[6] V. S. Sikarwar et al. “COVID-19 pandemic and global carbon dioxide emissions: A first assessment”. *Science of the Total Environment* 794, 148770 (2021).

[7] L. Whitmarsh, W. Poortinga, S. Capstick. “Behaviour change to address climate change”. *Current Opinion in Psychology* 42, 76–81 (2021).

[8] A. Tavoni et al. “Inequality, communication, and the avoidance of disastrous climate change in a public goods game”. *Proceedings of the National Academy of Sciences* 108, 11825–11829 (2011).

[9] C. E. Wagner et al. “Economic and behavioral influencers of vaccination and antimicrobial use”. *Frontiers in Public Health* 8, 614113 (2020).

[10] R. Holahan, P. Kashwan. “Disentangling the rhetoric of public goods from their externalities: The case of climate engineering”. *Global Transitions* 1, 132–140 (2019).

[11] A. Damodaran. *India, Climate Change, and the Global Commons*. Oxford University Press (2023).

[12] D. Andersson et al. “Dynamics of collective action to conserve a large common-pool resource”. *Scientific Reports* 11, 9208 (2021).

[13] J. J. Lawler et al. “1. Resource management in a changing and uncertain climate”. *Frontiers in Ecology and the Environment* (2010).

[14] G. Girardi, G. L. Preite. “Escaping the Economist’s Straightjacket: Overcoming the Free-Rider Mentality Which Prevents Climate Change from Being Effectively Addressed”. *Climate Change Research at Universities: Addressing the Mitigation and Adaptation Challenges*, 561–575 (2017).

[15] M. Lipsitch, M. H. Samore. “Antimicrobial use and antimicrobial resistance: a population perspective”. *Emerging infectious diseases* 8, 347 (2002).

[16] K. den Nijs et al. “A global sharing mechanism of resources: modeling a crucial step in the fight against pandemics”. *International Journal of Environmental Research and Public Health* 19, 5930 (2022).

[17] L. Yang et al. “Sociocultural determinants of global mask-wearing behavior”. *Proceedings of the National Academy of Sciences* 119, e2213525119 (2022).

[18] D. D. Heckathorn. “The dynamics and dilemmas of collective action”. *American sociological review*, 250–277 (1996).

[19] C. T. Bauch, D. J. Earn. “Vaccination and the theory of games”. *Proceedings of the National Academy of Sciences* 101, 13391–13394 (2004).

[20] J. Gupta et al. “A just world on a safe planet: a Lancet Planetary Health–Earth Commission report on Earth-system boundaries, translations, and transformations”. *The Lancet Planetary Health* 8, e813–e873 (2024).

[21] W. Rees. “What’s blocking sustainability? Human nature, cognition, and denial”. *Sustainability: Science, Practice and Policy* 6, 13–25 (2010).

[22] T. Oraby, V. Thampi, C. T. Bauch. “The influence of social norms on the dynamics of vaccinating behaviour for paediatric infectious diseases”. *Proceedings of the Royal Society B: Biological Sciences* 281, 20133172 (2014).

[23] J. Heitzig, K. Lessmann, Y. Zou. “Self-enforcing strategies to deter free-riding in the climate change mitigation game and other repeated public good games”. *Proceedings of the National Academy of Sciences* 108, 15739–15744 (2011).

[24] V. A. Karatayev et al. “A well-timed shift from local to global agreements accelerates climate change mitigation”. *Nature communications* 12, 2908 (2021).

[25] S. Barrett, A. Dannenberg. “Climate negotiations under scientific uncertainty”. *Proceedings of the National Academy of Sciences* 109, 17372–17376 (2012).

[26] E. H. Kaplan, D. L. Craft, L. M. Wein. “Emergency response to a smallpox attack: the case for mass vaccination”. *Proceedings of the National Academy of Sciences* 99, 10935–10940 (2002).

[27] X. Xu et al. “Should we remain hopeful? The key 8 weeks: spatiotemporal epidemic characteristics of COVID-19 in Sichuan Province and its comparative analysis with other provinces in China and global epidemic trends”. *BMC infectious diseases* 20, 1–15 (2020).

[28] L. Post et al. “Surveillance of the second wave of COVID-19 in Europe: longitudinal trend analyses”. *JMIR public health and surveillance* 7, e25695 (2021).

[29] J. White. “Climate change and the generational timescape”. *The Sociological Review* 65, 763–778 (2017).

[30] K. Vinke et al. “Corona and the climate: a comparison of two emergencies”. *Global Sustainability* 3, e25 (2020).

[31] J. Maloy. “Beyond Crisis and Emergency: Climate Change as a Political Epic”. *Ethics & International Affairs* 38, 103–125 (2024).

[32] T. Bickerstaffe. “A problem of generations? Habitus, social processes and climate change”. *Journal of Global Responsibility* 15, 111–124 (2024).

[33] D. K. Chu et al. “Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis”. *The lancet* 395, 1973–1987 (2020).

[34] S. A. Levin. “The problem of pattern and scale in ecology: the Robert H. MacArthur award lecture”. *Ecology* 73, 1943–1967 (1992).

[35] J. Chave. “The problem of pattern and scale in ecology: what have we learned in 20 years?” *Ecology letters* 16, 4–16 (2013).

[36] S. A. Levin. “Self-organization and the emergence of complexity in ecological systems”. *BioScience* 55, 1075–1079 (2005).

[37] I. D. Couzin et al. “Effective leadership and decision-making in animal groups on the move”. *Nature* 433, 513–516 (2005).

[38] G. S. Cumming, D. H. Cumming, C. L. Redman. “Scale mismatches in social-ecological systems: causes, consequences, and solutions”. *Ecology and society* 11 (2006).

[39] C. Folke et al. “The problem of fit between ecosystems and institutions: ten years later”. *Ecology and society* 12 (2007).

[40] R. DeFries, H. Nagendra. “Ecosystem management as a wicked problem”. *Science* 356, 265–270 (2017).

[41] C. Gulluscio et al. “Climate change accounting and reporting: A systematic literature review”. *Sustainability* 12, 5455 (2020).

[42] H. Lee et al. “Climate change 2023 synthesis report summary for policymakers”. *CLIMATE CHANGE 2023 Synthesis Report: Summary for Policymakers* (2024).

[43] A. Pirani et al. “Scenarios in IPCC assessments: lessons from AR6 and opportunities for AR7”. *npj Climate Action* 3, 1 (2024).

[44] A. Vespignani. “Modelling dynamical processes in complex socio-technical systems”. *Nature physics* 8, 32–39 (2012).

[45] H. W. Hethcote. “The mathematics of infectious diseases”. *SIAM review* 42, 599–653 (2000).

[46] D. J. Earn et al. “A simple model for complex dynamical transitions in epidemics”. *science* 287, 667–670 (2000).

[47] C. T. Bauch. “Imitation dynamics predict vaccinating behaviour”. *Proceedings of the Royal Society B: Biological Sciences* 272, 1669–1675 (2005).

[48] X. Chen, F. Fu. “Imperfect vaccine and hysteresis”. *Proceedings of the royal society B* 286, 20182406 (2019).

[49] K. E. Schnier. “Spatial externalities and the common-pool resource mechanism”. *Journal of Economic Behavior & Organization* 70, 402–415 (2009).

[50] H. Österblom, Ø. Paasche. “Earth altruism”. *One Earth* 4, 1386–1397 (2021).

[51] R. Boyd, P. J. Richerson. “Punishment allows the evolution of cooperation (or anything else) in sizable groups”. *Ethology and sociobiology* 13, 171–195 (1992).

[52] C. Wang, Q. Su. “Public goods games on any population structure”. *Science Advances* 12, eaeb1263 (2026).

[53] A. P. Galvani et al. “Human–environment interactions in population and ecosystem health”. *Proceedings of the National Academy of Sciences* 113, 14502–14506 (2016).

[54] C. Innes, M. Anand, C. T. Bauch. “The impact of human-environment interactions on the stability of forest-grassland mosaic ecosystems”. *Scientific reports* 3, 2689 (2013).

[55] B. L. Turner et al. “Illustrating the coupled human–environment system for vulnerability analysis: three case studies”. *Proceedings of the National Academy of Sciences* 100, 8080–8085 (2003).

[56] L.-A. Barlow et al. “Modelling interactions between forest pest invasions and human decisions regarding firewood transport restrictions”. *PloS one* 9, e90511 (2014).

[57] K. A. Henderson, C. T. Bauch, M. Anand. “Alternative stable states and the sustainability of forests, grasslands, and agriculture”. *Proceedings of the National Academy of Sciences* 113, 14552–14559 (2016).

[58] R. Cornes, T. Sandler. “Easy riders, joint production, and public goods”. *The Economic Journal* 94, 580–598 (1984).

[59] M. J. Kotchen. “Green markets and private provision of public goods”. *Journal of Political Economy* 114, 816–845 (2006).

[60] A. P. Galvani, T. C. Reluga, G. B. Chapman. “Long-standing influenza vaccination policy is in accord with individual self-interest but not with the utilitarian optimum”. *Proceedings of the National Academy of Sciences* 104, 5692–5697 (2007).

[61] M. Olson. *The Logic of Collective Action: Public Goods and the Theory of Groups*. Cambridge, MA: Harvard University Press (1965).

[62] A. Gelman, N. Silver, A. Edlin. “What is the probability your vote will make a difference?” *Economic Inquiry* 50, 321–326 (2012).

[63] N. L. Kerr. “Illusions of efficacy: The effects of group size on perceived efficacy in social dilemmas”. *Journal of Experimental Social Psychology* 25, 287–313 (1989).

[64] W. Sinnott-Armstrong. “It’s not my fault: global warming and individual moral obligations”. *Perspectives on Climate Change: Science, Economics, Politics, Ethics*. Ed. by W. Sinnott-Armstrong, R. B. Howarth. Vol. 5. Advances in the Economics of Environmental Resources. Emerald Group Publishing Limited, pp. 285–307 (2005).

[65] S. Kagan. “Do I make a difference?” *Philosophy & Public Affairs* 39, 105–141 (2011).

[66] M. Milinski et al. “The collective-risk social dilemma and the prevention of simulated dangerous climate change”. *Proceedings of the National Academy of Sciences* 105, 2291–2294 (2008).

[67] M. Tomasello. *Why we cooperate*. MIT press (2009).

[68] S. Bowles, H. Gintis. “Origins of human cooperation”. *Genetic and cultural evolution of cooperation* 2003, 429–43 (2003).

[69] T. A. Han, M. H. Duong, M. Perc. “Evolutionary mechanisms that promote cooperation may not promote social welfare”. *Journal of the Royal Society Interface* 21, 20240547 (2024).

[70] D. G. Rand, M. A. Nowak. “Human cooperation”. *Trends in cognitive sciences* 17, 413–425 (2013).

[71] M. Doebeli, C. Hauert. “Models of cooperation based on the Prisoner’s Dilemma and the Snowdrift game”. *Ecology letters* 8, 748–766 (2005).

[72] K. Wiesner, J. Puri, A. Reumann. “Complexity-Aware Monitoring And Evaluation Of Development Programs – Anchoring Them In Complexity Science”. *Advances in Complex Systems (ACS)* 27, 1–17 (2024).

[73] J. Ladyman, K. Wiesner. *What Is a Complex System?* Yale University Press (2020).

[74] O. P. Hauser et al. “Cooperating with the future”. *Nature* 511, 220–223 (2014).

[75] H. D. Matthews et al. “The proportionality of global warming to cumulative carbon emissions”. *Nature* 459, 829–832 (2009).

[76] D. J. Watts. “A simple model of global cascades on random networks”. *Proceedings of the National Academy of Sciences* 99, 5766–5771 (2002).

[77] T. Gross, C. J. D. D’Lima, B. Blasius. “Epidemic dynamics on an adaptive network”. *Physical Review Letters* 96, 208701 (2006).

[78] R. Pastor-Satorras, A. Vespignani. “Epidemic spreading in scale-free networks”. *Physical Review Letters* 86, 3200 (2001).

[79] J. Menard et al. “When conflicts get heated, so does the planet: coupled social-climate dynamics under inequality”. *Proceedings of the Royal Society B* 288, 20211357 (2021).

[80] R. Gifford. “The dragons of inaction: psychological barriers that limit climate change mitigation and adaptation.” *American psychologist* 66, 290 (2011).

[81] A. R. Pearson, C. G. Tsai, S. Clayton. “Ethics, morality, and the psychology of climate justice”. *Current Opinion in Psychology* 42, 36–42 (2021).

[82] M. Li et al. “Stimulating influenza vaccination via prosocial motives”. *PloS one* 11, e0159780 (2016).

[83] C. Betsch, R. Böhm, L. Korn. “Inviting free-riders or appealing to prosocial behavior? game-theoretical reflections on communicating herd immunity in vaccine advocacy.” *Health Psychology* 32, 978 (2013).

[84] N. A. Christakis, J. H. Fowler. “The spread of obesity in a large social network over 32 years”. *New England journal of medicine* 357, 370–379 (2007).

[85] J. M. Ortega-Egea, N. García-de-Frutos, R. Antolín-López. “Why do some people do “more” to mitigate climate change than others? Exploring heterogeneity in psycho-social associations”. *PLoS One* 9, e106645 (2014).

[86] C. L. Hanson et al. “Protection motivation during COVID-19: A cross-sectional study of family health, media, and economic influences”. *Health Education & Behavior* 48, 434–445 (2021).

[87] P. Marcuse. “Spatial justice: derivative but causal of social injustice”. *Spatial Justice* 1, 1–6 (2009).

[88] B. Jones, H. Rachlin. “Social discounting”. *Psychological science* 17, 283–286 (2006).

[89] K. A. Wade-Benzoni, L. P. Tost. “The egoism and altruism of intergenerational behavior”. *Personality and Social Psychology Review* 13, 165–193 (2009).

[90] M. Coleman, D. DeSteno. “Intertemporal empathy decline: Feeling less distress for future others’ suffering.” *Emotion* (2024).

[91] K. F. Law et al. “Ethical reasoning versus empathic bias: a false dichotomy?” *Trends in Cognitive Sciences* 28, 1–4 (2024).

[92] W. MacAskill. *Doing good better: How effective altruism can help you help others, do work that matters, and make smarter choices about giving back*. Penguin (2016).

[93] P. Singer. *The expanding circle*. Clarendon Press Oxford (1981).

[94] J. Z. Berman et al. “Impediments to effective altruism: The role of subjective preferences in charitable giving”. *Psychological science* 29, 834–844 (2018).

[95] P. Bloom. “Empathy and its discontents”. *Trends in cognitive sciences* 21, 24–31 (2017).

[96] L. Caviola, S. Schubert, J. D. Greene. “The psychology of (in) effective altruism”. *Trends in Cognitive Sciences* 25, 596–607 (2021).

[97] J. A. Everett et al. “The costs of being consequentialist: Social inference from instrumental harm and impartial beneficence”. *Journal of experimental social psychology* 79, 200–216 (2018).

[98] S. Lion, M. v. Baalen. “Self-structuring in spatial evolutionary ecology”. *Ecology letters* 11, 277–295 (2008).

[99] A. Avena-Koenigsberger et al. “Network morphospace”. *Journal of the Royal Society Interface* 12, 20140881 (2015).

[100] J. F. Donges et al. “Complex networks in climate dynamics: Comparing linear and nonlinear network construction methods”. *The European Physical Journal Special Topics* 174, 157–179 (2009).

[101] D. Centola, R. Willer, M. Macy. “The emperor’s dilemma: A computational model of self-enforcing norms”. *American Journal of Sociology* 110, 1009–1040 (2005).

[102] H. Bulkeley, M. Betsill. “Rethinking sustainable cities: Multilevel governance and the’urban’politics of climate change”. *Environmental politics* 14, 42–63 (2005).

[103] F. Padt, B. Arts. “Concepts of scale”. *Scale-sensitive Governance of the Environment*, 1–16 (2014).

[104] L. Shi et al. “Roadmap towards justice in urban climate adaptation research”. *Nature Climate Change* 6, 131–137 (2016).

[105] O. R. Young. “2. The problem of scale in human/environment relationships”. *Journal of Theoretical Politics* 6, 429–447 (1994).

[106] Z. Zhang et al. “Common pool resource governance in strong-government context: A case study of caterpillar fungus (Ophiocordyceps sinensis) on the Qinghai-Tibet Plateau”. *Environmental Science & Policy* 152, 103644 (2024).

[107] L. A. Nogueira, K. A. Wigger, S. Jolly. “Common-pool resources and governance in sustainability transitions”. *Environmental innovation and societal transitions* 41, 35–38 (2021).

[108] B. Adhikari. “The Economics of Common Pool Resources: A Review”. *Ecology, Economy and Society–the INSEE Journal* 4, 71–88 (2021).

[109] C. Tu et al. “Impact of resource availability and conformity effect on sustainability of common-pool resources”. *arXiv.org* abs/2310.07577 (2023).

[110] R. Way et al. “Empirically grounded technology forecasts and the energy transition”. *Joule* 6, 2057–2082 (2022).

[111] M. S. Sparks et al. “Health and equity implications of individual adaptation to air pollution in a changing climate”. *Proceedings of the National Academy of Sciences* 121, e2215685121 (2024).

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Data and code availability

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AI use statement

AI was used to edit simulation code and generate figures 2-4 and supplementary appendix figures.

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