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Climate change induced migration and the evolution of cooperation

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ABSTRACT

We study the impact of climate change induced migration on the evolution of cooperation using an *N*-player social dilemma game. Players in the population are divided into non-overlapped groups, and they can choose to either cooperate or defect within their group. At the same time, the players are mapped to the nodes of a scale-free network, enabling them to learn from the actions of players from other groups. Every player is allowed to migrate between groups, and their migration decisions are governed by the risk from climate change at the current group, as well as their ability to adapt. We introduce a cooperation threshold to ensure that a minimum percentage of players cooperate before any benefit can be achieved within a group. Comprehensive simulation experiments show that migration has a positive impact on the level of cooperation, and the cooperative behaviour observed is proportional to the threshold level. This study contributes by being one of the first to study climate change induced migration using evolutionary game theory. Our findings also contribute to the understanding of the impact of cooperation thresholds in promoting cooperative behaviour in multi-player social dilemma games, where players are allowed to migrate.

1. Introduction

Understanding the evolution of cooperation in a population of selfish individuals has been the goal of many scientific studies in fields such as biology, social sciences, economy, computer science, and physics. Social dilemma game models from evolutionary game theory (EGT) [1,2] offer a realistic interpretation of the way players with bounded rationality interact, and how cooperation emerges from their interactions. Given this, EGT has been used to study various real-world social phenomena such as migration [3–6], dynamics of changes in the population [7,8], and climate diplomacy [9,10].

Cooperative management and mitigation of climate change is a classical social dilemma, because cooperation that yields the best benefit for the human society is not in the best self-interest of individuals in the population. Using EGT to examine various aspects of climate change has led to studies on climate change governance [11], climate policies under wealth inequality [12], and climate change negotiations [10], among others. EGT has also been previously used to study various migration topics such as risk-driven migration [13], opportunistic migration [14], expectation-driven migration [15], immigration and assimilation into the host country's culture [16], and spread of group beneficial cultural variants through migration [17].

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Migration responses by humans to the impact of climate change are the result of a very complex combination of multiple pressures and opportunities that shape the behavioural decisions of individuals [18,19]. Evolutionary game models present a suitable medium for understanding how cooperation and coordination can be achieved for adapting to and mitigating climate change induced migration (CCIM) at the institutional level and among individuals. EGT makes it possible to illustrate the dilemmas and strategic options available to the various layers of actors. EGT, thus, can make the complex relationship between climate change and migration more transparent for decision-makers at the levels of governance and the public policy. The underlying EGT framework of climate change and migration can be seen as a model governing the struggle between different ideologies, policies, and responses to manage CCIM. Despite the promising potential of using EGT to study CCIM, and the continued research on migration and climate change separately using EGT, there have been no previous work, to the best of our knowledge, on the use of EGT to study CCIM.

Therefore, in this paper, we utilise EGT to study the evolution of cooperation under risk-driven migration, when climate change plays a central role in the decision-making process. We explore the evolution of cooperation in this context using an *N*-player social dilemma game, in the form of a Public Goods Game (PGG) [20]. Social dilemma games have been widely used to study cooperative phenomena [21], where cooperation is beneficial to the group in the long-term but is not the optimal option from an individual perspective in the short-term. In our PGG, cooperators share the cost of mitigation actions to prevent the impacts of climate change, whereas all players in the game benefit from the actions of cooperative players regardless of their actions. This abstract social dilemma model closely resembles the current climate change scenario where coordinating group efforts to mitigate climate change is beneficial in the long-term but sustaining cooperation is challenging because of low payoffs in the short-term, and even non-cooperators can benefit from the mitigation actions of others.

Specifically, the model we present simulates an environment where players in the population are divided into non-overlapped groups. At the same time, they are connected to other players through a scale-free network (i.e., a social network). Players in each group play the game and learn from their group members as well as connections in their social network. We also explore the effectiveness of cooperation thresholds [22], which specify the minimum level of cooperation that has to be present in the playing group before any benefit is achieved — higher the threshold, the more cooperators are required to derive any benefit. Our simulation results indicate that migration has a small but positive impact on the level of cooperation, whereas the improvement in cooperation is proportional to the cooperation threshold, with higher thresholds leading to higher levels of cooperation compared to lower thresholds. We further explore the impact of different initial group sizes on cooperation, with results indicating that larger initial group sizes might be more conducive for promoting cooperation.

The rest of this paper is organised as follows. In the next section, details of the model used in our study are described. The simulation results are then presented and discussed in Section 3. Finally, we draw conclusion in the last section.

2. Model

2.1. Game structure

We consider an *N*-player social dilemma game where interacting agents are divided into non-overlapped groups and are optionally connected with others through a scale-free social network. Each player (or agent), i, has a fixed ability to adapt to climate change, *adaptability*, α_i ($0 \le \alpha_i \le 1$). At every timestep, each agent takes an action based on its strategy $s_i \in \{C, D\}$, where C and D refer to cooperation and defection, respectively.

Each *group*, g, is simply a collection of agents, and an agent can only belong to one group at any given time. All groups have the same number of agents at initialisation, but their size, $|g|$, can vary with migration as the simulation progresses [23]. Fellow group members influence both the payoff and learning of an agent. This division is close to the concept of metapopulation, in which the overall population is allocated into several spatially separate subpopulations [24]. When considering the ability to adapt to climate change or the risk from climate change, each group is considered a distinct and whole unit—the individual players in the groups do not have separate values for those attributes.

Each group has an ability to adapt to climate change, α_g. In addition, each group has an associated risk from climate change, r_g, which is 0 for every group at initialisation and is updated at every timestep as follows:

$$r_g^{t+1} = r_g^t + \Delta r_g \, , \tag{1}$$

where r_g^{t+1} and r_g^t are the risks of group g at timestep $t+1$ and t, respectively. Δr_g is the change in risk and is calculated as follows:

$$\Delta r_g = \frac{x_g}{1 + e^{\alpha_g \cdot r_g}} \, , \tag{2}$$

where α_g and r_g are the adaptability and risk, respectively, of group g, and x_g is calculated as follows:

$$x_g = \begin{cases} -\frac{|g'|}{|g|}, & \text{if } \frac{|g'|}{|g|} \ge \alpha_g \\ (1 - \frac{|g'|}{|g|}), & \text{otherwise} \end{cases} \tag{3}$$

where $|g|$ and $|g'|$ are the total population of and the number of cooperators in the group, respectively. Note that even though group sizes are time-variable, we consider the group population or number of cooperators at the particular timestep t, and not over a time period.

Similarly, all agents in the model are mapped to the nodes of a social network, and the edges represent connections between the agents. The interaction between agents in the social network is limited to imitating the actions of other agents (or learning), and is further discussed in Section 2.3. Once created during initialisation, the network and its connections remain constant throughout the simulation, i.e., the social network is static.

2.2. Payoffs

As discussed previously, our social dilemma game strongly resembles a PGG. Therefore, benefits of the efforts put into mitigating climate change by the *cooperators* can be enjoyed by all the agents regardless of their actions. However, the costs of cooperation are borne only by the cooperators. Based on the above, an agent's payoff, p_i, is calculated using a Fermi rule [25] as follows [21]:

$$p_i = \begin{cases} b \cdot |g'| - \frac{c \cdot (|g|-1)}{|g'|+1}, & \text{for cooperators} \\ b \cdot |g'|, & \text{for defectors}, \end{cases} \tag{4}$$

where b, c, $|g|$ and $|g'|$ are the benefit from cooperation (per agent), overall cost of cooperation, the group's population, and the number of total cooperators in the group, respectively. Values of the parameters for the game must fulfil $b > c > 0$. The dilemma strength [26,27] in the game is thus quantified by $r = c/b$. Increasing c and decreasing b lead to a stronger dilemma; conversely decreasing c and increasing b lead to a weaker dilemma.

However, there are situations in the real-world where a minimum effort is required for some benefit to be achieved from the cooperative effort. An example, taken from [22], is the case of flood protection where a minimum number of individuals are required to set up an artificial dam for flood protection. If the required minimum number of individuals do not participate in the task, none of the agents (including the free-riders) receive any benefit. To this end, our model includes a threshold ratio, $0 < m \leq 0.5$, such that for a group of size $|g|$, any benefit is achieved only if the number of cooperators, $|g'|$, is at least $\lceil m \cdot |g| \rceil$. Now, an agent's payoff, when the threshold is not met, is calculated as:

$$p_i = \begin{cases} \frac{-c \cdot (|g|-1)}{\lceil m \cdot |g| \rceil} & \text{for cooperators}, \\ 0 & \text{for defectors}. \end{cases} \tag{5}$$

Even though all the groups initially have the same size, over the course of the simulation, the population of groups varies due to migration. Since an agent's payoff is dependent on the number of agents it interacts with (in this case the group members), the absolute payoff is biased towards agents with a higher number of connections [28]. Therefore, an agent's payoff is normalised on a scale of 0 to 1 based on the minimum and maximum possible payoffs in the group as follows:

$$\dot{p}_i = \frac{p_i - p_{min}}{p_{max} - p_{min}}, \tag{6}$$

where p_i, p_{min} and p_{max} are the absolute, minimum and maximum possible payoff values in the group, respectively. In any group, the minimum possible payoff is obtained by an agent, if it is the only cooperator in the group. Similarly, the maximum possible payoff is obtained by an agent, if it is the only defector in the group.

2.3. Agent strategy update

At the end of each timestep, after all agents have calculated their payoffs, each agent has an opportunity to update its strategy based on its and its neighbours' payoffs. The strategy update follows an evolutionary procedure based on imitation of neighbours and can be interpreted as information exchange in a social learning process [29]. The agents' actions follow a simple rule of conditional imitation: randomly pick a fellow group member or a connection in the social network, and conditionally imitate their last action (at timestep $t-1$) in proportion to their payoff. The probability of imitating the randomly chosen agent is determined as follows:

$$\mu = \frac{1}{1 + \frac{1}{e^{\eta(\dot{p}_o^{t-1} - \dot{p}_i^{t-1})}}}, \tag{7}$$

where μ is the probability of imitating the last action of the chosen agent, η is the background noise (a random value between 0 and 1), $\dot{p}_i^{t-1}$ is the current agent's normalised payoff, and $\dot{p}_o^{t-1}$ is the other agent's payoff at timestep $t-1$.

2.4. Agent movement

Individual agents can migrate from their current group to other groups to escape from groups with a higher risk of climate change. Migration decisions are made by individual agents at the end of each timestep. An agent considers migrating

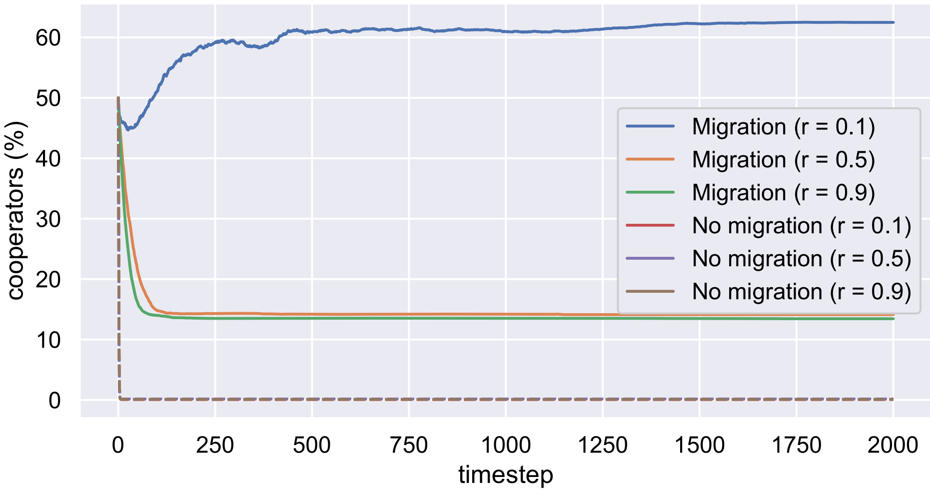

Fig. 1. Percentage of cooperators in the population throughout the simulation, with and without migration, averaged over 50 MC realisations. The population is divided into 100 groups for an initial group size of 10 each, the minimum cooperation threshold is 0, and there is no social network in place. Here, $r = c/b$, with the dilemma strength increasing as r increases from 0 to 1.

to another group if the current group's *risk from climate change* exceeds its *adaptability*, i.e., $r_g > \alpha_g$. Based on the restrictions on minimum and maximum allowed group sizes (see Section 2.1), migration away from the group is also forbidden if the group only has the minimum required members, and in-migration is not allowed if the destination group already has the maximum allowed members. The destination group can be any group in the model. This allows the population of groups to fluctuate during the simulation.

If the conditions for out-migration are met, the model allows for conditional migration, i.e., the agent can move to the destination group with a probability, μ, dependent on r at both the current group and the destination group as follows:

$$\mu = \frac{1}{1 + \frac{1}{e^{\eta(r_d - r_c)}}} \tag{8}$$

where μ is the probability of migration, η is the background noise (a random value between 0 and 1), and r_d and r_c are the risk of climate change at the destination and source groups, respectively.

3. Simulation results and analysis

Extensive numerical simulations were conducted to compare the equilibrium proportions of cooperative agents in the population across the spectrum of cost-to-benefit ratio $r \in [0 \ldots 1]$, and various levels of thresholds of cooperation ranging from 0 to 0.5. The size of each group, $|g|$, is restricted by $2 \le n \le 0.25 \cdot N$, where N is the total population of the model. This restriction on the minimum size of the group has been placed to avoid cases where groups consist of a solitary member. A maximum possible group size helps avoid cases where all agents congregate in one group; the 25% limit has been arbitrarily assigned in this study.

Each set of experiments was conducted with migration either allowed or disallowed. Similarly, each set of experiments was repeated either with social networks or no social network, with different initialisation parameters. Social networks were implemented using the Barabasi-Albert preferential attachment algorithm [30]. This algorithm adds new nodes to the network one at a time, and each new node is connected to M existing nodes with a probability that is proportional to the number of links the existing nodes already have. Higher the value of M, higher the density of the network. In our model, four different values of M were used: 2, 4, 6 and 8.

All the simulations were run for 5000 timesteps, with a population of 1000 individual players. Each simulation was repeated for 50 independent Monte Carlo (MC) realisations.

3.1. Impact of migration

The first series of simulations were run to study the impact of migration on cooperation within a population. In all these simulations, the initial group size was 10, the threshold m was set to 0, and there was no social network in place.

Fig. 1 shows the levels of cooperation (in %) throughout the population, for both with and without migration, averaged over 50 MC realisations. It is clear from the results that, when $r = 0.1$, migration can help promote cooperation in the population. Even for higher values of r, migration can help retain some level of cooperation. Without migration, cooperation cannot be sustained in the population, regardless of the cost-to-benefit ratio. Given the manner in which groups are divided

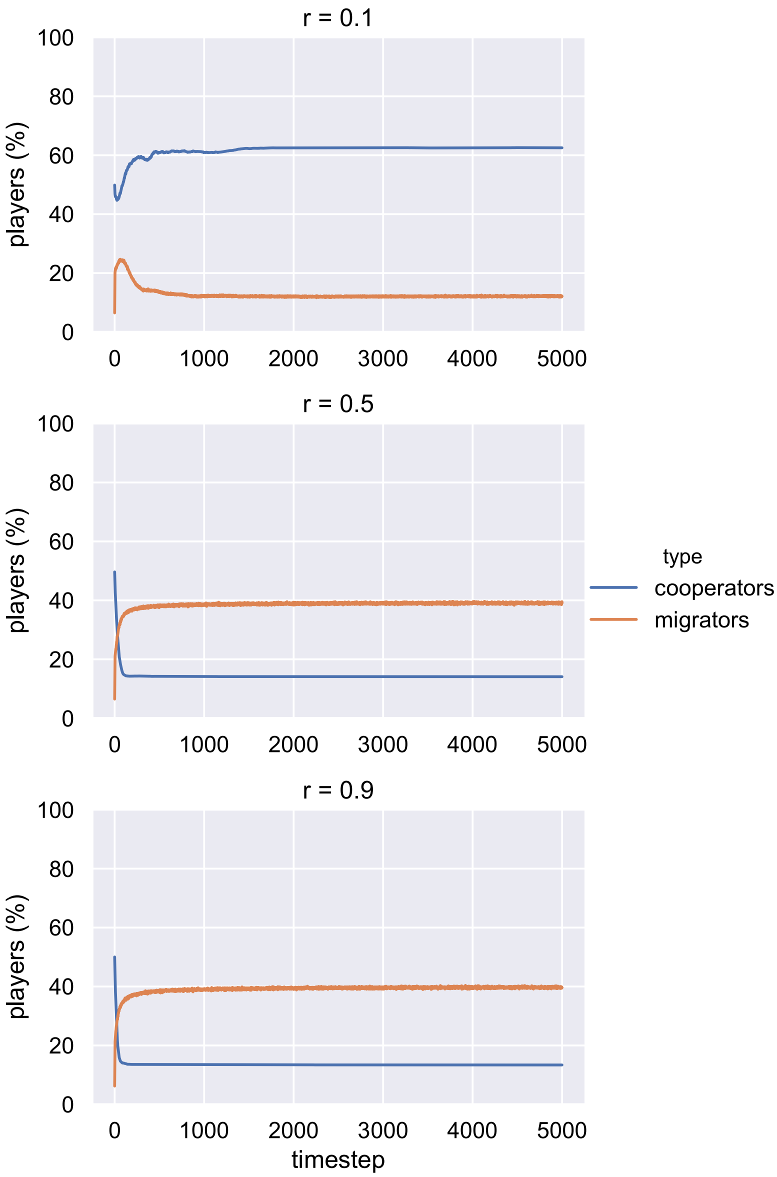

Fig. 2. Percentage of cooperators and migrators in the population throughout the simulation, averaged over 50 MC realisations. The population is divided into 100 groups for an initial group size of 10 each, the minimum cooperation threshold is 0, and there is no social network in place. Here, $r = c/b$, with the dilemma strength increasing as r increases from 0 to 1.

in our simulations, each group is similar to a well-mixed population and cooperation cannot be sustained in well-mixed populations. However, when migration is allowed from one group to the other, groups no longer represent well-mixed populations and therefore cooperation is sustained in the population.

However, at the same time, results also indicate that migration needs to be controlled. Fig. 2 shows the relationship between cooperation and migration, when migration is allowed, for the same set of conditions as above. The results show that an increase in the level of migration corresponds to a drop in the level of cooperation. It can be observed that when migration is allowed, the levels of cooperation and migration are inversely proportional to each other, i.e., more the migration less the level of cooperation. An observation common to both Figs. 1 and 2 is that when r is sufficiently high, there is very little difference in the level of cooperation in the population. The levels of cooperation and migration both are consistent for high values of r (0.5 and 0.9 in this case).

Even though cooperation can be sustained in the entire population, the same cannot be said for individual groups. It can be seen in Fig. 3 that while migration leads to groups of varying population sizes, they are all either full of cooperators or defectors. While Fig. 3 shows only three individual MC realisations, the same observations were made for all 50 MC realisations: every group at the end of the simulation contained either only cooperators or defectors.

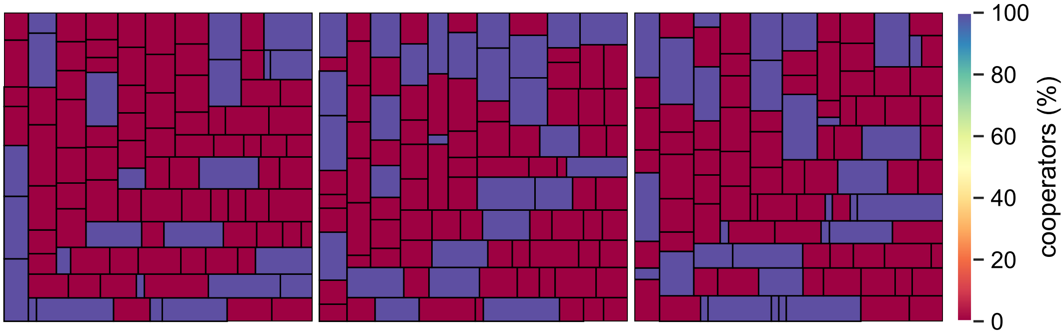

Fig. 3. Percentage of cooperators and group sizes, at the end of the simulation, in each group for three different MC realisations. Each subplot represents an individual MC run. Each rectangle in the subplots represents a group, with the size of the rectangle corresponding to the number of players in that group. Similarly, the colour of the rectangle indicates the level of cooperation in the corresponding group.

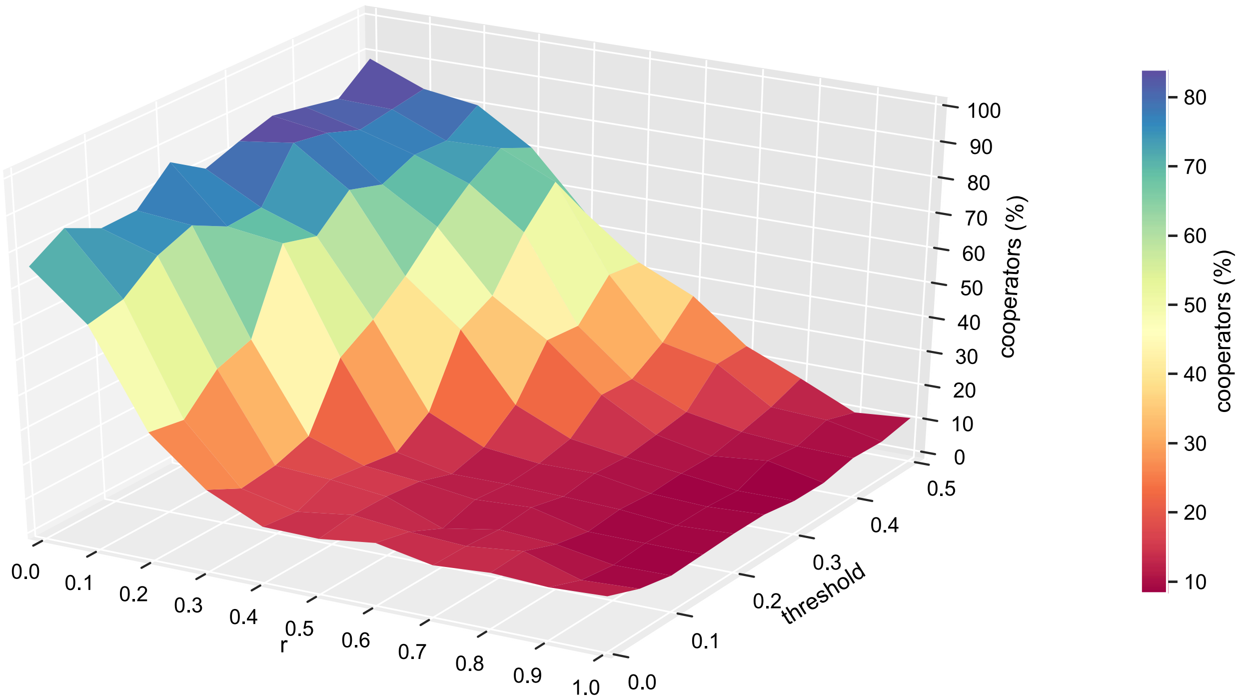

Fig. 4. Percentage of cooperators in the population as a function of $r = c/b$ across different thresholds. The minimum percentage of cooperators required for benefits to be achieved increases with the increasing threshold. Here, the population is divided into 100 groups for an initial group size of 10 each, migration is allowed, and there is no social network in place. All data points are averages over 50 MC realisations.

3.2. Impact of thresholds

The above discussion has established that controlled migration has a positive impact on the level of cooperation. In the following series of experiments, thresholds were introduced to study how the level of cooperation would be impacted if a minimum number of cooperators were required for any benefit to be achieved. The threshold values used in this study are: 0, 0.1, 0.2, 0.3, 0.4 and 0.5. A threshold of 0.0 means no minimum threshold is required for benefits to be received and 0.5 means at least half of the agents had to cooperate for anyone to receive benefits.

Fig. 4 shows the percentage of cooperators in the population with migration allowed, and various values of thresholds. The results show that higher the threshold, more the improvement in the level of cooperation, with the advantage of threshold narrowing down as the cost-to-benefit ratio r increases. In fact, with very high r, the level of cooperation achieved without any threshold is as good as (or better than) some lower threshold values. However, it can be safely assumed that having a higher level of threshold required for anyone to receive the benefits of cooperation will serve to increase the level of cooperation.

The impact of threshold on cooperation is further illustrated in Fig. 5, which shows the relationship between cooperation and migration as a function of r and threshold. It is clearly observed from the plots that the impact of higher thresholds is

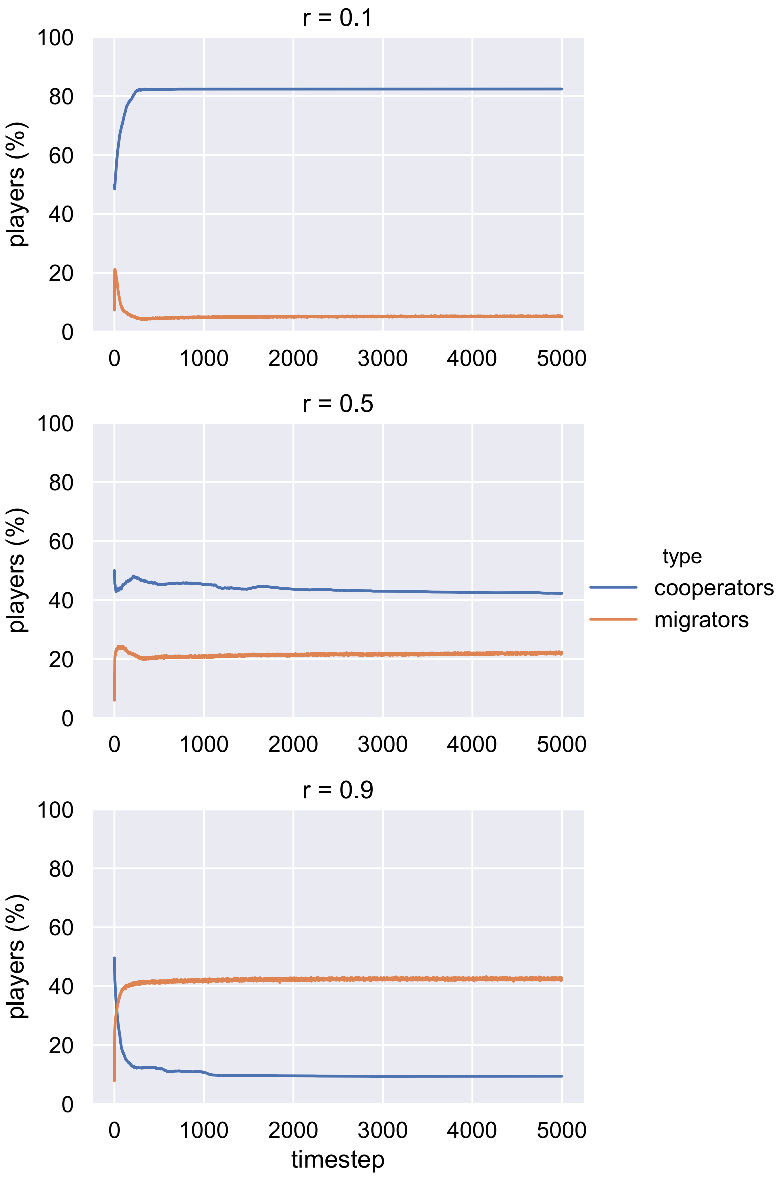

Fig. 5. Percentage of cooperators and migrators in the population, for the maximum threshold (0.5), throughout the simulation, averaged over 50 MC realisations. The population is divided into 100 groups for an initial group size of 10 each, migration is allowed, and there is no social network in place. Here, $r = c/b$, with the dilemma strength increasing as r increases from 0 to 1.

more noticeable for lower values of r. Whereas the level of cooperation without migration was the same for high values of r (0.5 and 0.9), as seen in Fig. 2, this is not the case when thresholds are introduced in the model.

3.3. Impact of social network

In the two previous subsections, the simulation results have demonstrated that both migration and thresholds help improve the level of cooperation in the population and, as expected, the improvement is more pronounced when the cost is minimal and less pronounced when the cost is very high. The simulations conducted so far did not have an additional layer of connection between agents in different groups. The next set of simulations was conducted to study the impact of social network on cooperation. In these experiments, social networks were constructed with four different densities by using different values of the 'attachment parameter', M = 2, 4, 6 and 8; and they are henceforth referred to as $SN(M)$, with M representing the density of the scale-free network.

It can be observed from Fig. 6 that, with higher thresholds, the level of cooperation achieved with a social network in place is initially better than, or at least as good as, when players are not connected in a social network. However, the levels of cooperation achieved with and without a social network are reversed with an increase in the cost of cooperation. With

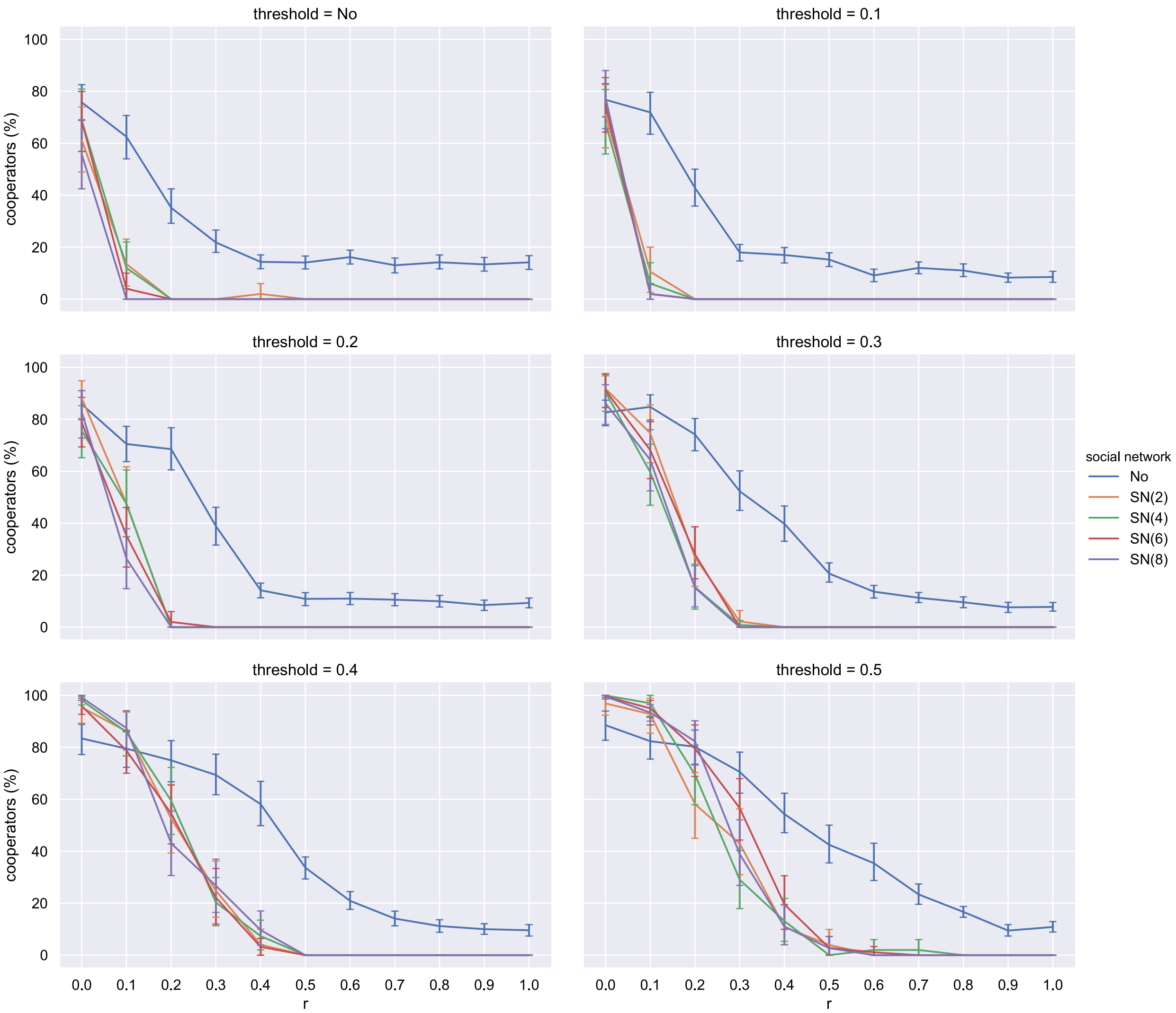

Fig. 6. Percentage of cooperators in the population as a function of $r = c/b$, different threshold values and different social network settings. Here, SN(2), SN(4), SN(6) and SN(8) refer to social networks with m parameter values as 2, 4, 6 and 8, respectively.

increasing threshold values, the cost-to-benefit ratio at which the 'no social network' setting becomes more conducive for cooperation than a social network also increases. Regardless, for most cost-to-benefit ratios, the absence of a social network is, in general, more favourable for cooperation and helps retain some cooperative behaviour even for very high cost-to-benefit ratios. For higher ratios, the difference in the level of cooperation is quite pronounced. Another observation is that the variation in construction of a social network makes minimal difference, even for very high thresholds.

There are a few explanations for the above phenomenon. With social networks and the spread of information, agents learn that defection pays more than cooperation, especially as the cost of cooperation increases. Given that the social 'connections' are possibly spread over a number of groups, they are more likely to influence only a player's learning and less likely to influence its payoff (unless they are in the same group). If the information that social connections help spread is highly unlikely to influence themselves, such information does not facilitate cooperative behaviour. With denser social networks, the probability of socially connected agents belonging to the same physical group will be higher. In such cases, social network connections will influence each others' payoff in addition to learning. Regarding the minimal difference in the impact of the social network's attachment parameter, one explanation is that the possibility of social 'connections' influencing each others' payoffs and the faster spread of information in denser networks balance each other out.

3.4. Impact of initial group sizes

Fig. 7 shows the impact of initial group sizes on the evolution of cooperation. It can be seen that the level of cooperation is higher for larger initial group sizes compared to smaller initial group sizes, regardless of the threshold or social network

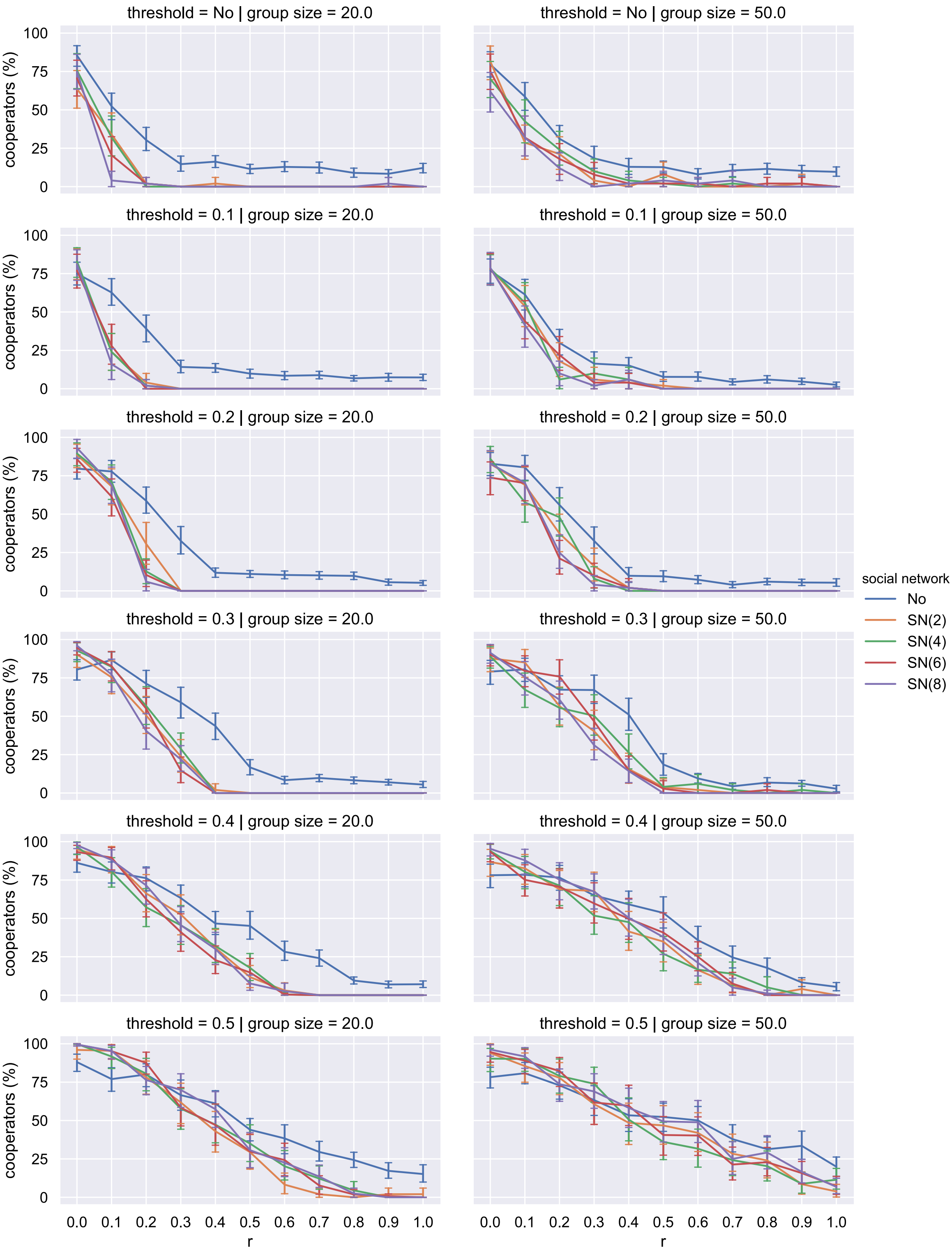

Fig. 7. Percentage of cooperators in the population for different values of $r = c/b$ for different social network settings. Different rows and columns correspond to different thresholds and initial group sizes, respectively. The population is divided into 100 groups with an initial group size of 10 each. All data points are averages over 50 MC realisations.

settings. In addition, larger initial group sizes are able to retain cooperation even at very high levels of cost-to-benefit ratios. The impact of social network settings is also more pronounced for larger initial group sizes. With the default simulation settings when the initial group size is 10 (see Fig. 6), social networks with different attachment values are equally conducive for cooperation only for low cost-to-benefit ratios. In contrast, social networks are as conducive for cooperation as the 'no social network' setting for larger group sizes. In fact, for group size 50, the levels of cooperation achieved with all social settings are comparable.

Despite the fact that group sizes can fluctuate during the simulation because of migration, the results indicate that the initial group sizes play a role in promoting cooperation. This can be explained by the number of options available to an agent when considering migration. Since the overall population is the same throughout, larger group sizes mean fewer groups. For players considering migration, there are fewer groups to choose for migration decisions when the initial group sizes are larger compared to when the initial group sizes are smaller. Additionally, this behaviour is also influenced by social networks. With smaller initial group sizes, a player's connections in a social network are likely to be spread over a number of groups. However, with larger initial group sizes, social network connections have a higher probability of being members of the same physical group. It will help to recall that, in our model, a player's payoff is only impacted by the actions of others in the same physical group and a social network connection, which influences the player's learning, will only impact its payoff if they are in the same group. Given this, with fewer groups, it is more likely that at least some of a player's social-network connections are in the same physical group and thus impact its payoff. This is a sensible explanation for the comparable performance of all social network settings for all cost-to-benefit ratios in larger initial group sizes when such performance was comparable only at low cost-to-benefit ratios in smaller initial group sizes.

4. Conclusion

In this paper, we have used an N-player social dilemma game based on the PGG to study the evolution of cooperation under the influence of CCIM. Players make their migration decisions based on the risk from climate change at their location and their ability to adapt. As is common to the PGG, benefits from cooperation are enjoyed by all players whereas the costs of mitigating actions are borne only by the cooperators. Targeted simulations across a range of cost-to-benefit ratios, cooperation thresholds, social network settings and initial group sizes were run to explore the impacts on the evolution of cooperation due to migration, thresholds, social networks, and initial group sizes. Simulation results showed that some level of controlled CCIM can facilitate the promotion of cooperative behaviour in the population under suitable conditions. Results also indicated that cooperation thresholds, and initial group sizes and social networks can either individually or, as a combination, further promote cooperative behaviour. To summarise, the following interpretations can be drawn:

- Migration has a positive impact on the level of cooperation; however, less the migration higher the cooperative behaviour. In contrast, the impact decreases with higher cost-to-benefit ratios.
- Higher thresholds have a positive impact on the level of cooperation, and this phenomenon is observed even with very high cost-to-benefit ratios. Lower thresholds, however, do not have a significant advantage over the no threshold scenario.
- The impact of social networks is dependent on both thresholds and initial group sizes. While social networks, by themselves, do not appear to be more conducive for cooperation compared to the case without social networks, social networks can further promote cooperation when having higher thresholds or larger initial group sizes.
- The initial size of the groups in the population also impacts the level of cooperative behaviour observed: larger initial group sizes facilitate cooperative behaviour more than smaller group sizes. Even though the size of each group fluctuates with migration, it appears that larger initial group sizes indirectly promote cooperation by reducing the number of migration options available to the players.

Even though migration and climate change have been studied separately by other researchers in the EGT literature, the use of EGT to study CCIM has not received much attention. Our study demonstrated the applicability and potential of EGT to study CCIM. Future work can focus on integrating different migration dynamics and mechanisms that have been studied in the literature such as trust [31,32]. How cooperation can be used to manage and mitigate CCIM is also of great interest and deserves further highly targeted and comprehensive studies. Using real-world data to validate the model (e.g., see [33,34]) regarding CCIM is another possible research venture.

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