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Seeding leading cooperators and institutions in networked climate dilemmas

Manuel Chica [a,b,*], Francisco C. Santos [c]

[a] Andalusian Research Institute DaSCI "Data Science and Computational Intelligence", University of Granada, 18071 Granada, Spain
[b] School of Electrical Engineering and Computing, The University of Newcastle, Callaghan, NSW 2308, Australia
[c] INESC-ID & Instituto Superior Técnico, Universidade de Lisboa, 2744-016, Porto Salvo, Portugal

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ABSTRACT

Global cooperation poses problems shaped by the effects of stakeholders' decisions on future losses, and how collective risks are perceived. Institutional sanctioning of free-riders may prevent widespread defection in this context. Yet, the prevalence of such institutions represents another second-order dilemma, often as tricky as the tragedy of the commons we aim to avert. Here, we combine evolutionary game theory with techniques widely used in marketing to find, target, and seed leaders and institutions' promoters to boost cooperation in climate dilemmas. By doing so, we identify the increase in cooperation when introducing a heterogeneous networked population and the conditions under which seeding policies can ensure the self-organization of cooperation and stable institutions. Counter-intuitively, we show that seeding a small fraction of institutional supporters at random network positions practically is as good policy as seeding highly central players in climate dilemmas. We show that cooperation and institutions prevalence are mainly determined by the interaction network and, to a less extent, by imitation ties, and that seeding cooperators only offers marginal benefits when compared with directly seeding sanctioning institutions. Our study also presents a way of incorporating costs when deciding the best policy to apply. Finally, this work suggests that the potential benefits of seeding and targeting techniques are not exclusive to collective dilemmas and can be applied to other dilemmas having structured populations.

1. Introduction

From COVID-19 restrictions [1,2] to climate change decisions [3], averting catastrophic events often requires individuals to cooperate for the collective good [4]. This is challenging in climate social dilemmas as there is a need for a contribution, tempting free-riders to take advantage on the efforts of others [5]. Here, the key element is balancing selfish interests and common good [6]. An example when mitigating climate change is the decision of cutting carbon emissions, which is one of the most important applications of climate dilemmas [6–12]. One way to facilitate cooperation is having strong local institutions, which are important for the successful governance in public good games (PGGs) [13].

In fact, the role of local institutions to solve the second-order free riding problem (i.e., establishing institutions to punish free-riders) has been a useful tool for promoting cooperation [3]. In the latter work, the study of a collective-risk dilemma (CRD) [14,15] demonstrated the importance of both local and global institutions for increasing the agreement achievement of the public groups. Specifically, CRDs are multiplayer PGGs where every player can contribute with some amount to avoid a certain risk of failure. Nevertheless, institutions are not enough to avoid free-riders in climate dilemmas and more interventions are needed [16].

Opinion leaders are an overlooked complement to these efforts to mitigate future risks such as those of climate change [17]. According to [17], an appropriate climate change-related campaign can combine the strength of recruiting and targeting digital opinion-leaders and traditional media strategies, always having a clear communication goal for the population. The need of leader voices for public good resources and the creation of institutions is not a unique feature of climate dilemmas. Human experiments also show that mechanisms behind avoiding collective risks depend on an interaction between behavioral type, communication, and timing [6]. Andersson et al. [18] showed evidence on the role of voluntary local leadership in the creation of new institutional arrangements for governing shared natural resources using human experiments. They claim voluntary local leaders initiate self-governance institutions because leaders can directly affect local users' perceived costs and benefits associated with self-rule.

However, the role of leadership in environmental governance remains under explored both theoretically and empirically [18]. Yet

* Corresponding author at: Andalusian Research Institute DaSCI "Data Science and Computational Intelligence", University of Granada, 18071 Granada, Spain.
E-mail addresses: manuelchica@ugr.es (M. Chica), franciscocsantos@tecnico.ulisboa.pt (F.C. Santos).

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while marketing practitioners and scholars are actively targeting opinion leaders [19–22], researchers on climate dilemmas and evolutionary games remain strangely disconnected from these industry trends [17]. For instance, viral marketing campaigns consist of targeting certain consumers to encourage a faster product's adoption [23,24]. The selection of these influentials is not a random but a complex optimization process that involves the analysis of the social network of consumers to trigger a large cascade of adoptions thus favoring a positive information diffusion [25]. This computational problem is known as influence maximization [26].

There are some previous works on leadership in evolutionary human experiments and computational games. Droz et al. [27] point out that the motion of the influential players can improve remarkably the maintenance of cooperation. Leaders who behave too selfishly may induce people to do the same and may nurture people's beliefs that others will do the same; then, role models will affect the evolution of cooperation [28]. In the evolutionary model of Kang et al. [28], an asymmetric PGG is defined with two roles, influencers and followers, placed in a spatial lattice. Influencers have an extra gain in both their cooperating and defecting strategies. In another recent study [29], an evolutionary game with leadership by example is defined by including influential leaders as an additional strategy in the game, who set an example for others in the group. However, none of them applies seeding strategies to leaders neither in PGGs nor climate dilemmas.

The overall goal of this study is to understand the effects of seeding leaders on the dynamics of climate dilemmas using evolutionary game theory [30]. These leadership cannot be understood without the inclusion of peers' relationships and social networks [19,31,32]. Therefore, we first introduce a networked population in a CRD with local institutions by employing artificial social networks [33]. The use of heterogeneous networks to promote cooperation was proposed in social dilemmas since the works of Santos and Pacheco [34], as the emergence of cooperative clusters in the hub nodes who have a large number of neighbors are occupied by the cooperators. But the dynamics of CRDs in heterogeneous networked populations were not studied comprehensively up to this date. Chen et al. [35] studied the impact of CRDs in spatial structured populations, where players have a limited interaction range. In the latter model, the distribution of assets of the population could be tuned by means of an allocation strength parameter. Previously, the implications of having migrant players to move through a lattice was studied in a CRD model [36].

An heterogeneous networked population will allow the study of players' leadership with respect to both the number of groups they are involved and their social ties with other players. After studying the leadership role of players, this work applies seeding strategies by fixing the strategies of leaders during the simulation, a novel proposal in CRDs and evolutionary games. Targeted players will act as either cooperating leaders or punishers to influence other players during the course of the simulation, being able to generate a cascade of cooperation. Afterwards, we evaluate if fixing leaders at the most connected nodes of the network enhances cooperation and establishes local institutions.

Through a complete set of experiments, we compare homogeneous and heterogeneous network topologies for the CRD with respect to a well-mixed (WM) population. We study differences on leadership to understand the effects of the network heterogeneity in the output of the dilemma from different perspectives: from groups involvement to social imitation. Finally, the simulations will show if seeding leaders can help to solve the second-order free riding problem and how we can promote cooperation by engineering seeding policies. Finally, a method to calculate the costs of these policies is also included as a managerial insight.

The networked CRD model, seeding leaders policies, update rule, and simulation-based methods are shown in Section 2. Main results for the comparison between WM and networked populations with institutions are given in Section 3. Section 4 provides the analysis of leadership, seeding strategies, and the cost to implement them. The paper ends with the concluding remarks and implications of the study in Section 5.

2. Methods

The networked CRD with punishing local institutions and seeding players are first modeled in Section 2.1. Later, the evolutionary update strategy is described in Section 2.2. Section 2.3 defines the simulation-based methods and experimental setup used for the experiments.

2.1. Definition of the networked CRD with seeds

The networked CRD model with institutions includes a finite number Z of players who play in groups of heterogeneous size. Every player i can choose its strategy $s_i(t)$ among three different alternatives at every time step t, until reaching a maximum of T steps: cooperation (C), punishing (P), and defection (D). Cooperators pay a cooperation cost c for sustaining the public good of the group and help to reduce the risk of failure r. Punishers are cooperators who additionally pay a tax π_t to create a punishing institution in the group k. Finally, defectors only benefit from the group without contributing anything, free-riding from others' cooperation.

Some players from population Z, defined as a sub-population Z^*, are seeds, targeted as part of targeting strategies to promote cooperation by leadership. A seed $i^* \in Z^*$ has a fixed cooperating strategy for the whole simulation. A player i^* can be a cooperating seed ($s_{i^*}(t) = C, \forall t \in \{1,\dots,T\}$) or a punishing institutional seed ($s_{i^*}(t) = P, \forall t \in \{1,\dots,T\}$).

All the players, both regular and seeds, interact in groups. In the traditional CRD without structured population, a player i only belongs to a group, and all the groups have the same size [2]. However, in the networked CRD model, players can interact in different groups of heterogeneous size. This is because each focal player i creates a group with their local contacts in the network but also participates in the groups formed by their contacts in the network. Thus, a player i will participate in $\langle k \rangle_i + 1$ groups, being $\langle k \rangle_i$ the degree of the node of player i in the network. See Fig. 1 for an illustrative example of the groups formation.

Every group faces a risk probability $r \in [0,1]$. This risk of failure happens when the number of cooperators j_C and punishers j_P in the group does not achieve a minimum threshold n_{pg}. When there are enough punishers in a group (j_P), given a minimum threshold of punishers n_p, the members of the group can create a local institution for the group by using the tax π_t of every punisher. Then, defectors must pay a penalty or fine π_f. Taking into account these dilemma definitions, the expected payoff for each of the three strategies, Π_C, Π_P, and Π_D, are equivalent to the proposed in [3] and given by:

$$\Pi_C = -c + \Theta(j_C + j_P - n_{pg}N) + (1-r)(1-\Theta(j_C + j_P - n_{pg}N)), \tag{1}$$

$$\Pi_P = \Pi_C - \pi_t, \tag{2}$$

$$\Pi_D = \Pi_C + c - \delta, \tag{3}$$

where N is the size of the specific group and δ is a local punishment function being $\delta = \pi_f \Theta(j_P - n_p N)$. $\Theta(x)$ is the Heaviside step function, equals to 0 whenever $x < 0$ and equals to 1 otherwise. A player i will accumulate its payoff in Π_i from the $\langle k \rangle_i + 1$ groups it plays in a networked population (note that a player only belongs to one group under WM conditions). Finally, we have assumed that the initial endowment of each player is set to 1.

2.2. Strategy update of the regular players

After playing a game at time-step t, regular players can update their strategies according to the received payoffs. In contrast, the seeded players of Z^* have time-invariant strategies. However, both of them can interact in their groups and they can be imitated by the rest of the

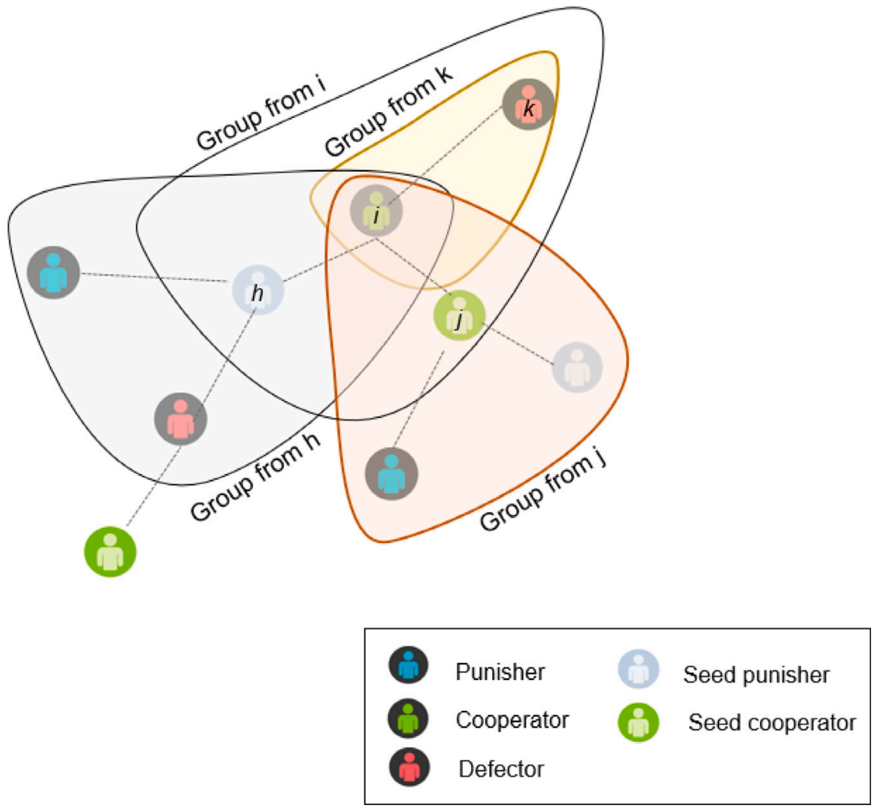

Fig. 1. Illustration of a network of players forming and playing in heterogeneous groups. Players can be either regular or seeded players. Regular can adopt the three different strategies and seeds keep their cooperation or punishing strategies.

players. The only difference of seeded players with respect to regular players is their inability to update their strategies.

Regular players can evaluate and update their strategies by following the Fermi function as their evolutionary update rule [37,38]. The Fermi rule is a stochastic pairwise comparison rule in which strategies that do well, are more likely to be imitated, and spread throughout the population. At each time-step, a regular player i with a payoff Π_i can revise its strategy. In case of a network structure is considered, the player j is selected from the set of local contacts in the network. A random player j from the population is chosen at random if having a WM population. Player i will imitate the strategy of j with a probability p that increases with their payoff difference — $(\Pi_j - \Pi_i)$ — and can be written as in [38]:

$$p = \frac{1}{1 + e^{-\beta(\Pi_j - \Pi_i)}}. \tag{4}$$

The free parameter β is the intensity of selection, encoding the chance of mistakes during the imitation process. This means that a player i can copy another player's strategy j despite having a lower payoff. We set $\beta = 5$ in all the experiments of the study. The dynamics of the game also includes a mutation function to randomly change the strategies of the regular players at every time step t. A regular player i changes its strategy at random with a mutation probability μ and imitates the strategy of a local neighbor with probability $1 - \mu$.

2.3. Agent-based computational methods and experimental setup

The experiments are based on Monte-Carlo (MC) agent-based simulations [25,39], performed in computer clusters to obtain the stationary states of the model specifications. The simulation software is programmed in Java and available at the following repository.[1] Evolution proceeds in discrete steps involving the payoffs accumulation for all the groups each player takes part and social imitation through update rules within the whole population or specific network. All the specifications of the model are run for 150 independent MC realizations and for a maximum number of 10^3 synchronous time steps, reaching a stationary stable state and having a low MC realizations' deviation. The presented results were obtained by averaging the last 25% of the simulation time steps in the independent MC realizations.

We employ a population of $Z = 5 \times 10^3$ in all the experiments. The mutation (or exploration) probability μ is set to 0.01. With respect to the CRD settings, minimum thresholds for coordination n_{pg} and contribution n_p to create an institution in a group are set to 0.75 and 0.25, respectively. Contributing tax for punishers is set to $\pi_t = 0.03$ while fine for defectors when an institution is created is set to $\pi_f = 0.3$, as done in previous studies [3]. Equal distribution of the playing strategies in the population are normally considered ($Z_C^0 = Z_P^0 = Z_D^0$) The rest of the parameters of the game are specified in the respective sections and resources.

Finally, we define two performance indicators to show the achievement of the groups of the population, as done in [3]. First, we define group achievement, η_G, as the ratio of groups having a minimum number of cooperators and punishers (i.e., $j_C + j_P \geq n_{pg} N$). Second, we define institutions prevalence η_I as the ratio of groups where their local institutions have been maintained (i.e., $j_P \geq n_p N$) and thus, defectors can be sanctioned by the punishing institution.

3. Results on networked CRD with institutions

In this section we first compare cooperation levels for the CRD with and without network structure in Section 3.1. We further explore, in Section 3.2, the main insights from the networked CRD by studying the need of institutions in addition to the network structure. No seeding strategies are used in this experimentation and then, no seeded players are included ($Z^* = \emptyset$).

[1] https://bitbucket.org/mchserrano/seedingcrds.

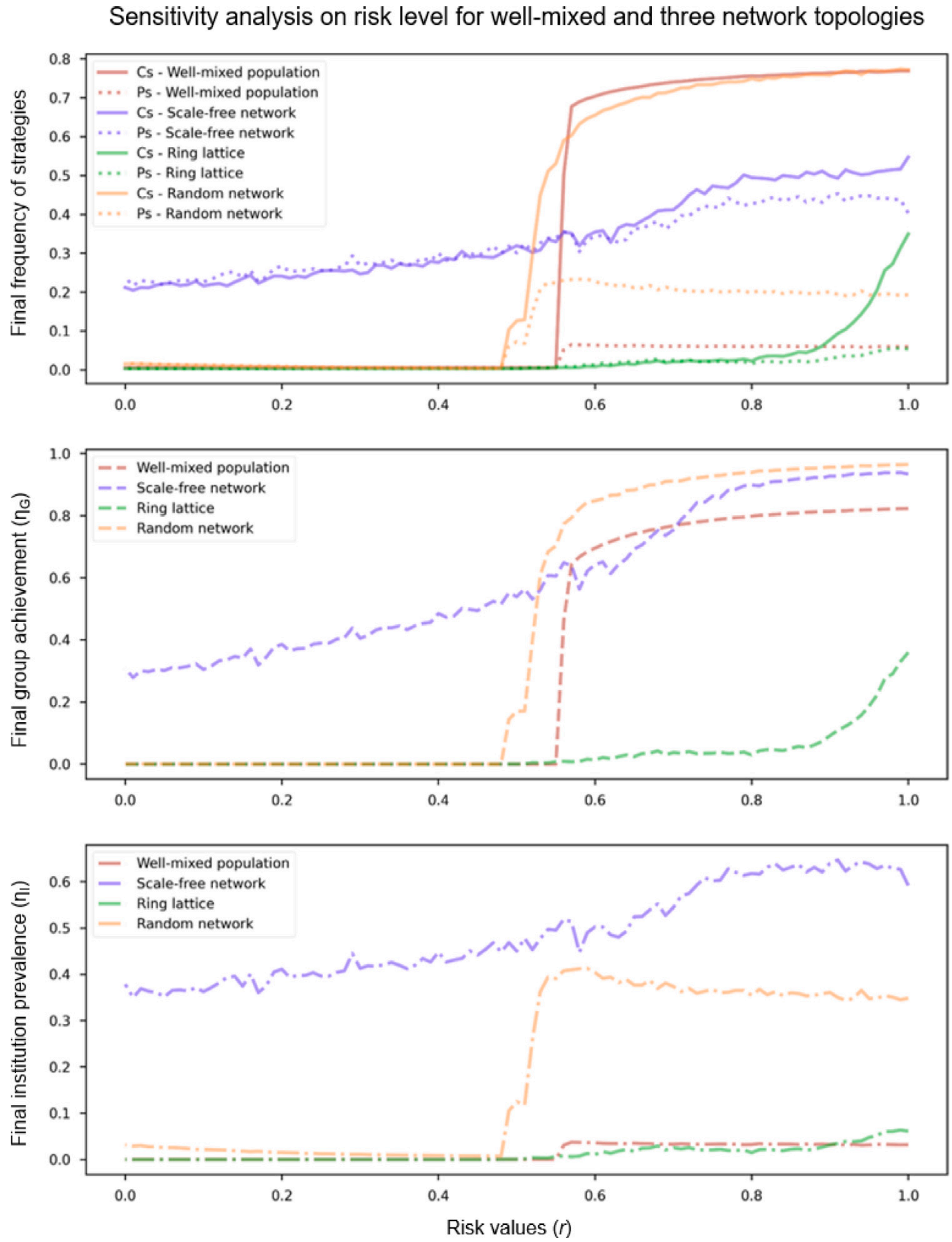

Fig. 2. Sensitivity analysis on risk r when $c = 0.25$ for WM population and three network topologies with different heterogeneity (SF, RL, RN). Plots show heterogeneous networks better promote the final frequency of cooperating strategies (C and P), η_G, and η_I. Specifically, SF networks obtains significant increases when risk values are low.

3.1. A comparison between well-mixed and networked populations

We study there the dynamics of the game in a WM population with respect to networked populations. As explained in Section 2, the network will condition the number of groups each player is involved as well as the contacts to imitate by the social update rule. We use three different network topologies with different heterogeneity levels: scale-free (SF) networks, ring lattice (RL), and random network (RN). The three topologies have similar average degree $\langle k \rangle \approx 4$ and density (0.004). Concretely, we use the Barabasi–Albert algorithm [40] (we set $m = 3$ for the algorithm) to generate SF networks with an average degree of 4. The small-world rewiring algorithm [41] is employed with both probability values $p = 0$ and $p = 1$ to generate the RL and RN, respectively. In order to avoid anomalous network artifacts, we employ different SF networks for the MC runs. For the WM population, the size of the randomly formed groups are set to $N = 4$ to have similar group size then the averaged group size of the networked settings.

We perform a sensitivity analysis on the probability of risk failure r for a cooperation cost $c = 0.25$ to compare the four population structures. Fig. 2 shows the final number of strategies in stationary state as well as group achievement (η_G) and institution prevalence (η_I) for the three network topologies and well-mixed configuration. The results show that having a heterogeneous SF network increase the number of cooperators and punishers when risk is low or nonexistent. When risk probability r is lower than 0.5, WM configuration and less heterogeneous networks (i.e., RL and RN) end up in a population with full defection. On the contrary, the SF network is able to maintain a 40% of the institutions and a group achievement η_G between 60% and 30%. When the risk increases and thus, the game becomes easier, the RN obtains identical results than SF network. The RL is not able to reach any level of cooperation until the highest value of r. When the game is in a transition zone (i.e., a risk value between 0.5 and 0.75), RN and even a WM population can reach slightly higher cooperation than SF networks.

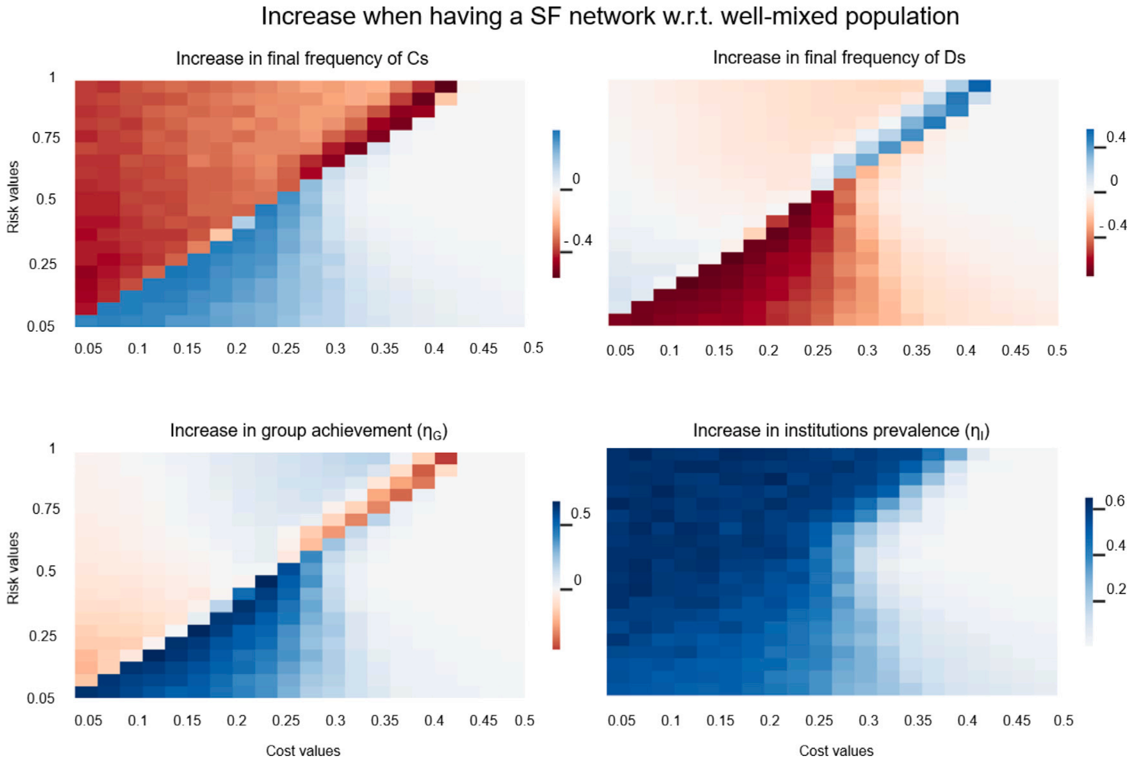

Fig. 3. Heatmaps comparing positive differences when having SF structure with respect to WM for final cooperators and defectors (η_G and η_I). Values are obtained from a two-parameters sensitivity analysis on risk r and cost c. SF structure enhances the creation of institutions but, in the absence of these institutions and in the transition phase, a WM configuration can better promote cooperation. Thus, adding a network structure is not always beneficial for cooperation.

To have a clearer map on the cooperation increase and institutions prevalence when adding a SF network, we plot the difference between having a SF network with respect to the WM configuration. The analysis is done by a two-parameters sensitivity analysis on both risk r and cost c. Fig. 3 shows four heatmaps (final cooperators, final defectors, η_G, and η_I) for the positive difference of having a SF network with respect to a WM population. Institutions are initiated for all the values of risk when including a SF network (bottom-right heatmap of Fig. 3). With a WM configuration, cooperation is only achieved by cooperators as punishers cannot prevail. Group achievement η_G, shown in the bottom-left heatmap of the figure, is also significantly better when incorporating a SF network in the CRD model.

However, as shown in [42] when dealing with games having co-existence strategies such as the snowdrift, adding a network structure is not always beneficial for all the parameters' configuration. Heatmaps of η_G and final defectors in Fig. 3 show that the WM configuration is better than SF network for values of risk higher than 0.5 and cost higher than 0.25. In this space of the transition zone, WM achieves higher cooperation in the absence of institutions. Nevertheless, the surface on η_G for both parameters shows that heterogeneous networks such as a SF network can solve the second-order CRD and generates states with higher levels of cooperation than WM and less heterogeneous networks. Institutions are clearly better established in the population when having a SF structure.

3.2. The need of both institutions and network to solve the second-order free riding problem

The use of heterogeneous networks in the CRD is clearly increasing both η_G and η_I. Thus, a SF network can solve the second-order free riding problem. However, one can ask if a networked population is sufficient to obtain high levels of cooperation and therefore, punishing players and local institutions are not needed. In order to investigate the latter concern, we perform a sensitivity analysis on (r, c) when having no institutions but a structured population. By running this experiment, the question of needing institutions apart from a networked population can be answered.

Specifically, the experiments of a sensitivity analysis on risk levels r and cooperation costs c are carried out for two configurations: (a) a CRD with a SF network and only two strategies (either cooperation or defection) and (b), a CRD with a SF network but adding punishing players to sustain institutions. Initial conditions are the same for both configuration and a mutation probability set to 0. However, 66% of the initial population of configuration (a) are cooperators for a fair comparison with respect to configuration (b).

Fig. 4 shows three heatmaps for the difference on final frequency of defectors, group achievement (η_G), and institution prevalence (η_I). We can clearly see how punishing institutions decrease defectors in the whole population (top-left heatmap) and then, η_G is significantly increased up to 75% when high cost c and high risk. The group achievement η_G metric is dominated by the model with institutions in the whole transition zone. The bottom heatmap (η_I) is also interesting to see as it highlights the surface of the sensitivity analysis where institutions are more necessary. These results confirm that not only heterogeneous networks promote cooperation in CRDs but institutions are needed.

4. Analysis of leadership and seeding policies for the CRD

Through this part of the experimental study we first study in Section 4.1 the role of leadership and heterogeneity of the groups. Second, Sections 4.2 and 4.3 show the results when applying seeding strategies and their implementation costs.

4.1. Evaluating leadership for playing and social imitation

From the point of view of CRDs with heterogeneous networks, we can understand leaders as those located in the hubs of the network.

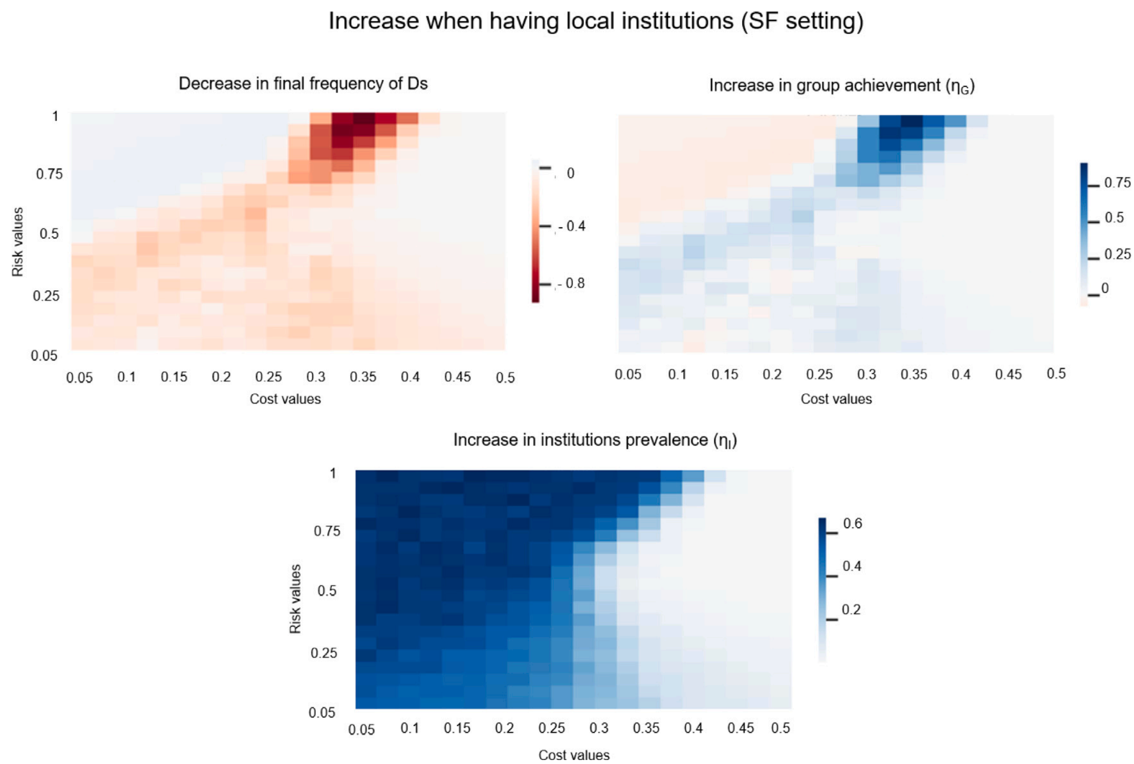

Fig. 4. Heatmaps comparing the difference when having institutions (i.e., punishing players) with respect to a CRD without institutions (both settings with a SF network). Plots show differences for the final frequency of defectors, η_G, and η_I. Values are obtained from a two-parameters sensitivity analysis on risk and cost. The reader can clearly observe how local institutions are needed to promote cooperation for a SF setting.

However, the influence of leading players could arise from two mechanisms: First, from the high number of groups they play on and second, from the social imitation and cascade process they generate from their position in the network. In this experiment we evaluate two model specification of a networked CRD with a SF network. The first specification includes both leading mechanisms (leaders and, by extension, all the players in the population will play in a heterogeneous number of groups and influence direct contacts from the network). The second specification of the model will remove the leadership of the hubs in the social imitation process [20] by only considering leadership in the number of groups they play on. Thus, the second setting considers the evolutionary update rule of Section 2.2 as in a WM population or a full-connected network.

Fig. 5 shows a heatmap of a sensitivity analysis on r and c comparing leadership and heterogeneity just on groups or both in groups and social imitation. We can see how results change depending on the values of pair (r, c). When the game is easier (higher values of risk and cooperation cost), the influence of the hubs and leaders for the update rule is not helping to promote cooperation. We can observe how when $r > 0.5$ and $c > 0.25$, the network structure and the influence of social leaders is less beneficial for cooperation in terms of η_G and even institutions prevalence η_I. These results are in line with the behavior observed with the WM configurations in Section 3.1.

Nevertheless, leadership for social imitation (i.e., update rule) through the SF structure is supportive for cooperation and institutions when having low risk values and medium and high cooperation costs. In this scenario of hard conditions for cooperation because of the low risk of failure, social leadership associated to the presence of hubs in the SF network can boost cooperation. As observed when comparing WM and SF configurations in Section 3.1, the output of the game can be different depending on the game conditions, again in line with previous studies [42].

4.2. Impact on targeting seeding leaders and institutions

In this experiment, under equal initial conditions (i.e., 33% of each strategy in the population and same parameters), we hypothesize with the effects on seeding a small group of seeds (either cooperators or punishers) at the beginning of the simulation. This seeding process is either targeting leaders (i.e., hubs or central nodes in the SF network) or targeting random players. The goal is to understand if these seeds are able to generate a cascade effect on the rest of the population. As defined in the game in Section 2.1, seeded players will keep their strategy (either C or P) for the whole simulation. These seeds are not increasing the proportion of strategies in the initial conditions of the simulation as they are part of the three sub-populations of players by always maintaining $Z_C^0 = Z_P^0 = Z_D^0$.

Fig. 6 shows values for η_G and η_I when seeding punishers and cooperators at the beginning of the simulation. We compare four alternatives: (i) seeding punishing leaders (hubs in the SF network, decreasingly ordered by their degree), (ii) seeding punishing players at random in the network, (iii) seeding cooperator leaders (same order by degree as in (i)), and (iv) seeding cooperators at random in the population. The results of Fig. 6 are obtained by two pairs of values of (r, c): $(0.6, 0.3)$ and $(0.5, 0.35)$.

From the results of both configurations we can observe how seeding punishing individuals (either leaders or random players) dramatically achieves important levels of cooperation because of their support to institutions. These strategies can obtain higher cooperation than targeting cooperators. Thus, by just targeting around 6% of the players as punishers, we achieve more than 75% of η_G in the case of $(r = 0.6, c = 0.3)$. When risk is lower and cost is 0.35, the baseline (no seeding strategy) stuck in $\eta_G = 0$. By seeding 10% of the population as punishers, we obtain a group achievement of 0.6 and an institution prevalence of 0.7. We have to remind that all the initial conditions remain as in the baseline (no seeding). By seeding cooperators instead of punishers, the impact is minor and the increase in η_G is only noticeable in the

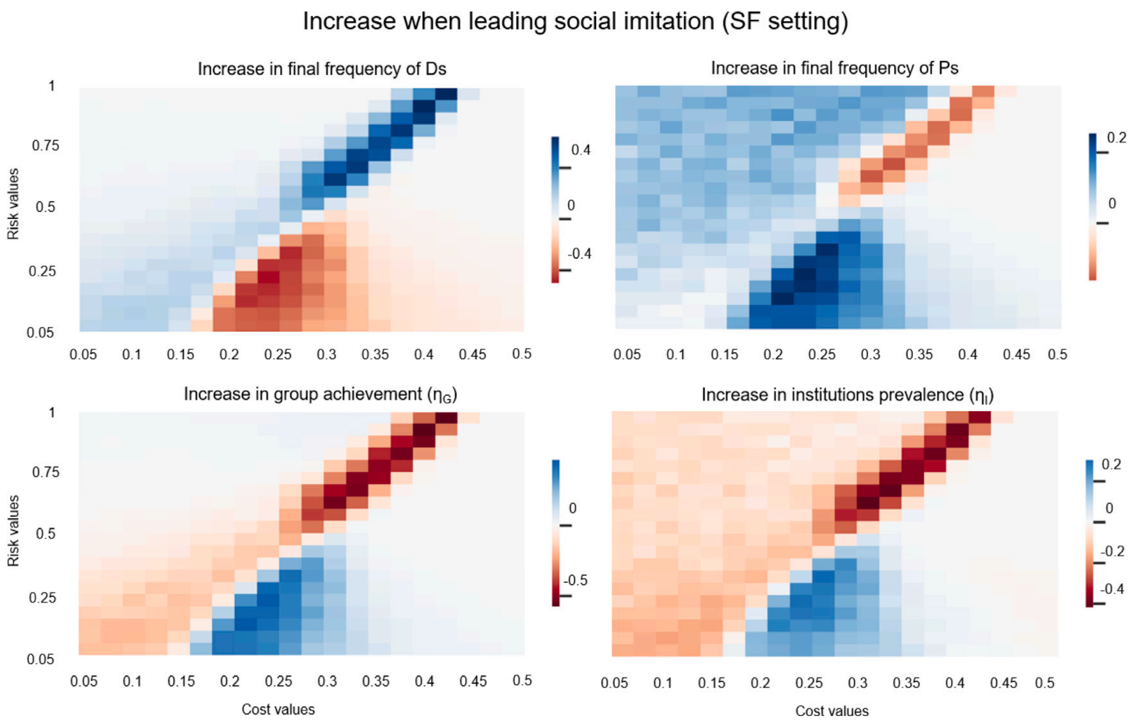

Fig. 5. Heatmaps comparing two CRD models with SF network with and without imitation leadership. Values of the heatmaps are obtained from sensitivity analysis on r and c, and they show the final frequency of Ds, Ps as well as final η_G and η_I. Leadership is supportive for cooperation under hard conditions of the game (mainly, low risk values and medium-high cooperation costs).

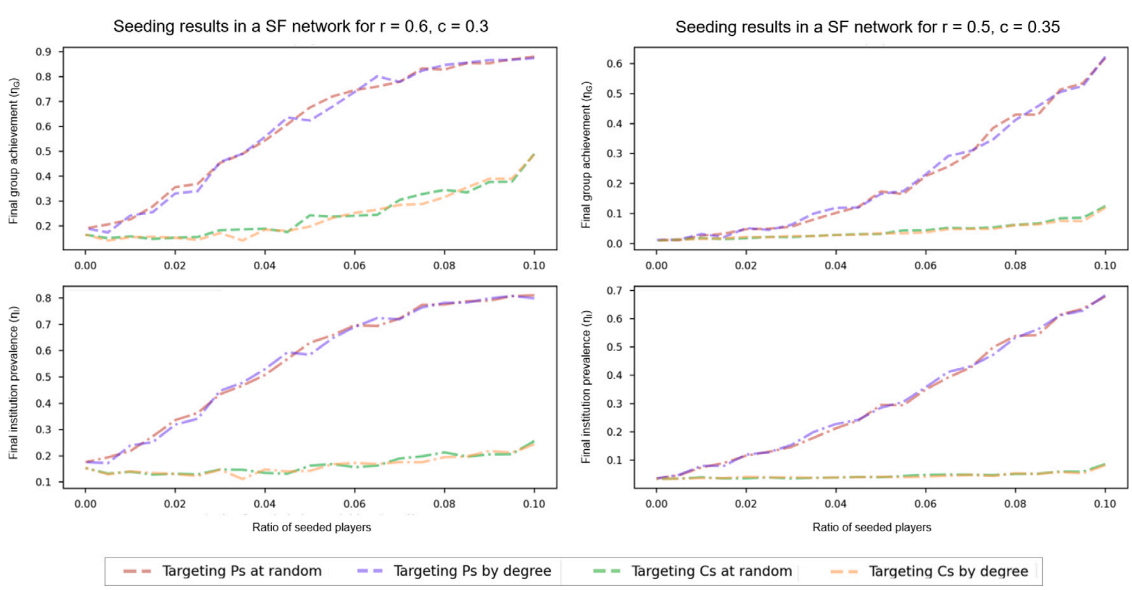

Fig. 6. Final values of metrics η_G and η_I when seeding punishers and cooperators for two pairs of (c, r): $(0.3, 0.6)$, $(0.35, 0.5)$ at random and by leadership in the SF network (i.e. hubs). Seeding punishers better promotes cooperation, while the use of a network degree-based policy is not adding benefits.

scenario of ($r = 0.6, c = 0.3$) and after seeding 6% of the population as cooperators.

In this specific CRD, counter-intuitive results are obtained with respect to seeding leaders as no important differences are given. However, we already explored in previous Section 4.1 how social imitation pushed by leaders through the use of the network was not significantly important or, at least, it does not boost cooperation for all the model conditions. The comparison showed that results are equivalent and therefore, the heterogeneity of the network is increasing cooperation mostly because of the diversity of the groups than the social influence of the evolutionary update rule.

4.3. Managerial costs of seeding leaders and institutions

Finally, we show the implementation costs that occur when seeding players. We calculate the cost to pay each seeded player by taking into account the number of groups the targeted player is playing during the simulation (just one time for all the time-steps T). Then, we multiply the number of groups by cooperation cost c in the case of seeding cooperators and by $(c + \pi_t)$ in the case of being a punisher (i.e., we add the tax the punisher pays even if the institution cannot be created).

Fig. 7 shows the costs increase as a function of the ratio of seeded players. These results are able to picture that seeding leaders is more

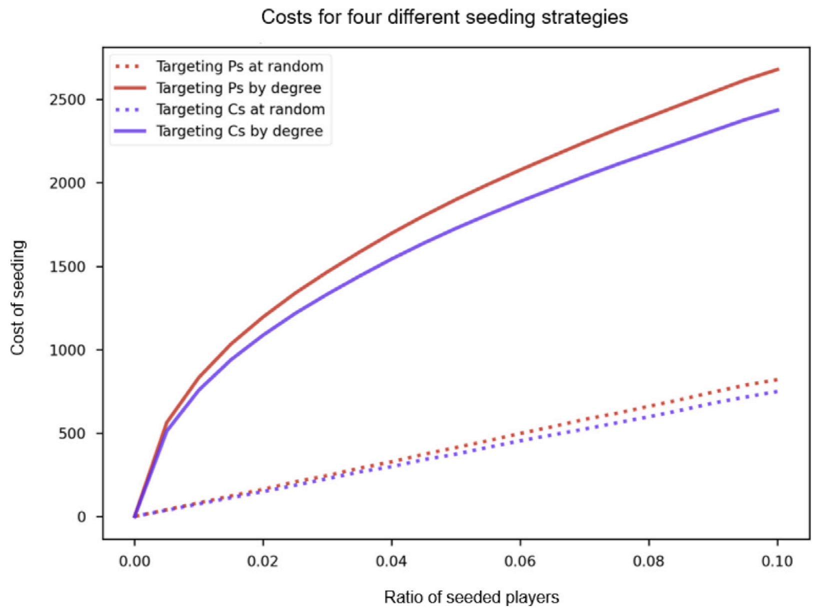

Fig. 7. Cost evolution depending on the ratio of seeds in four strategies: (a) targeting punishers at random nodes of the network, (b) targeting punishers at the hubs, (c) targeting cooperators at random and d), targeting cooperators at the hubs of the network. Targeting players by degree is always more costly as players are involved in more groups. A random seeding strategy is more affordable in terms of saving costs when launching the policy.

expensive than targeting players at random. The reason is they play in more groups and the costs both for institutions and cooperation are higher. In the specific case of CRDs, as group achievement η_G is equivalent, seeding leading players in the hubs of the network is more expensive but does not influence much. As seeding cooperators do not contribute to create institutions and the effect on cooperation is lower than seeding punishers, the economic efforts to target punishers can be justified from a managerial point of view.

5. Concluding remarks

Managing leaders and institutions are important to deal with climate change challenges. One way to model and understand decisions in climate change actions is by means of climate dilemmas, normally modeled by evolutionary games. In this paper we have proposed the use of seeding techniques, widely used in marketing and other fields, to target and seed those leaders and institutions' promoters to boost cooperation in climate dilemmas.

To do so, we first enriched the CRD with a social network and added heterogeneity in both groups and social imitation to be closer to model leadership. We empirically observed that the use of social networks generally increased cooperation and helped to solve the second-order free riding problem. Heterogeneous networks such as the SF topology are the ones obtaining the highest institutions prevalence and groups' achievement. The main positive differences obtained by the SF network are found when the risk of failure r is low. Apart from the social network, the use of local institutions are needed to create a synergistic effect.

By taking the networked CRD with local institutions, we recreated four different seeding strategies to target both cooperators and punishers at random and at the most connected nodes of the network. We found out that, for this specific CRD, leadership with respect to the network's connections are not crucial and it also comes at a cost (i.e., higher seeding costs as hubs play in more groups). The experiments also demonstrated that seeding punishers, those players supporting local institutions, are significantly more profitable than seeding cooperators. By just seeding a small ratio of seeded punishers between 6% and 8% at the beginning of the simulation, we can shift the whole system from a null group achievement to an almost full cooperation state under the same initial conditions.

The application of seeding strategies to evolutionary games based on the location of the players in a network, their personalities, strategies, and goals, among other features, is not restricted to climate dilemmas. In this study, we open a path to engineer evolutionary games with this type of interventions to favor cooperation and solve existing dilemmas. Nevertheless, we acknowledge that this work also presents limitations. First, we applied the seeding strategies to a specific CRD with local institutions and showed seeding hubs in the network are not worthy. However, this result cannot be applied universally and seeding leaders and key players must be further studied. Another limitation and then, opportunity for future works, is to further develop the idea of leadership in evolutionary games. Apart from some limited works [28, 29], most of the efforts were done with human experiments [18]. We think the study of leadership and seeding strategies in other PGGs and network topologies might be of interest [43].

CRediT authorship contribution statement

Manuel Chica: Software, Methodology, Validation, Investigation, Writing – original draft, Funding acquisition. **Francisco C. Santos:** Conceptualization, Methodology, Formal analysis, Writing – review editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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