

Highlights

Evolution of cooperation among fairness-seeking agents in spatial public goods game

Hong Zhang

- Introduces fairness-driven mobility in spatial public goods games (SPGG).
- Moderate movement rates enhance cooperation by forming stable cooperative clusters.
- Excessive movement disrupts clusters, increasing defector dominance and reducing cooperation.
- Empty sites play a crucial role in forming and stabilizing cooperative dynamics.

Evolution of cooperation among fairness-seeking agents in spatial public goods game

Hong Zhang^{a,*}

^a*Center for Economic Behavior & Decision-Making (CEBD), and School of Economics, Zhejiang University of Finance and Economics, Hangzhou, 310018, China*

Abstract

The evolution of cooperation is a pivotal area of study, essential for understanding the survival and success of complex biological and social systems. This paper investigates the dynamics of cooperation in spatial public goods games (SPGG) through a model that incorporates a fairness-driven migration mechanism. In this model, agents move towards environments perceived as fairer, influencing the spatial distribution and overall level of cooperation within the population. We examine the interplay between the time scale ratio, noise in movement, and population density. Our analysis reveals that moderate levels of movement and noise are critical for forming and maintaining cooperative clusters, while excessive movement and noise disrupt these structures, leading to reduced cooperation. Higher enhancement factors increase the resilience of cooperative behavior, extending the range of movement intensity over which high cooperation levels are maintained. Population density significantly impacts cooperative dynamics, with high-density environments promoting the coexistence of cooperators and defectors but lowering the highest achievable cooperation levels due to increased exploitation. Our findings underscore the importance of balancing movement, noise, and density to sustain cooperation and stable social structures. This research provides valuable insights for designing interventions and policies to promote cooperative behavior and social cohesion in complex populations. Future studies should further explore the adaptive mechanisms that dynamically adjust movement and strategy adaptation based on local environmental conditions.

Keywords:

*Corresponding author

Email address: poyeker@gmail.com (Hong Zhang)

1. Introduction

The evolution of cooperation is a cornerstone of scientific inquiry because it underpins the survival and success of complex biological and social systems. Understanding how cooperation evolves is crucial for explaining the emergence of complex behaviors and societal structures in both human and non-human species [1, 2, 3]. In biological contexts, cooperative behaviors can enhance survival rates, facilitate resource sharing, and improve reproductive success. For instance, cooperative hunting strategies in animals or symbiotic relationships between species demonstrate how cooperation can provide mutual benefits that outweigh individual efforts [4]. In human societies, cooperation is the bedrock of social cohesion, enabling the development of communities, economies, and cultures [5, 6, 7, 8, 9, 10, 11]. Furthermore, insights into cooperative dynamics have profound implications for fields such as evolutionary biology, psychology, economics, and artificial intelligence, offering solutions to contemporary challenges such as climate change, resource distribution, and conflict resolution. By exploring the mechanisms and conditions that foster cooperation, scientists can better understand the evolutionary processes that shape behavior and contribute to the advancement of societal well-being [12, 13, 14, 15, 16].

To explain the evolution of cooperation, researchers have identified five main mechanisms that support cooperative behavior [17]: kin selection [18, 19], direct reciprocity [20, 21, 22], indirect reciprocity [23, 24, 25], network reciprocity [26, 27, 28, 29], and group selection [30, 31, 32, 33]. Kin selection operates on the principle that individuals are more likely to cooperate with relatives to increase the survival of shared genes, a concept formalized by Hamilton's rule. Direct reciprocity involves repeated interactions between the same individuals, where cooperation is maintained through the expectation of future mutual benefit, famously encapsulated in the "tit-for-tat" strategy. Indirect reciprocity extends this concept to larger social networks, where individuals gain reputational benefits from being seen as cooperative, thus encouraging others to cooperate with them. Network reciprocity suggests that cooperation can emerge in structured populations where individuals interact more frequently with their neighbors, forming clusters of cooperators that can resist invasion by defectors. Lastly, group selection posits that groups of cooperators can outcompete groups of defec-

tors, leading to the proliferation of cooperative traits across populations.

These mechanisms collectively provide a robust framework for understanding the diverse ways in which cooperation can evolve and be maintained in various contexts. A crucial factor in these mechanisms is assortative interaction [34], where cooperators preferentially interact with each other. This selective interaction increases the likelihood of mutual benefits, reduces exploitation by defectors, reinforces cooperative behavior, promotes trust, and helps sustain cooperation within populations. Assortative interaction creates a supportive environment where cooperation can thrive and be maintained over time.

In addition to the five main mechanisms, mobility has emerged as a significant factor influencing the evolution of cooperation [35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47]. Mobility refers to the ability of individuals to move within a population, which affects their interactions and the formation of cooperative clusters. When individuals can move freely, they can escape from defectors and seek out other cooperators, thereby enhancing the overall level of cooperation in the population. This dynamic process allows cooperators to aggregate and form stable clusters, which can resist invasion by defectors and promote cooperative behavior over time. Research has shown that mobility can facilitate the formation of cooperative groups by allowing individuals to preferentially interact with others who are also cooperative. For example, research has shown that in mobile populations, individuals tend to form clusters of cooperators, resulting in higher levels of cooperation compared to static populations [35]. Additionally, studies have highlighted that mobility can enhance the robustness of cooperation against random fluctuations and invasions by defectors, thus stabilizing cooperative behavior over the long term [36]. These findings suggest that mobility is a crucial mechanism that enhances the evolution of cooperation by enabling cooperators to self-organize and form resilient cooperative networks.

The relationship between fairness and the evolution of cooperation has been extensively explored in evolutionary biology and social sciences, highlighting its critical role in fostering and maintaining cooperation within and across species. Fairness plays a pivotal role in promoting cooperative behavior by penalizing unfair tactics, as demonstrated by unbending strategies in the Iterated Prisoner's Dilemma [48]. The necessity to be chosen as a cooperative partner has driven the evolutionary origins of equity, creating selection pressure for behaviors that maximize individual fitness through fairness [49]. Experimental findings suggest that fairness varies with ethnic homogeneity and market integration, indicating that it evolved as a strategy to support cooperation in diverse social environments [50]. Additionally, evolutionary

game models reveal that heterogeneous networks, facilitated by oxytocin, enhance fairness and cooperation on a global scale, underscoring the importance of network structures and neurobiological factors [51]. Research on primates further supports these findings, showing that only chimpanzees, not orangutans, exhibit aversive reactions to unfairness, implying that fairness sentiments may have evolved convergently in species with complex social systems [52]. Collectively, these studies underscore the importance of fairness in the evolution of cooperation, highlighting its significance in promoting stable and cooperative interactions across various contexts.

Traditional mobility mechanisms in the evolution of cooperation typically focus on migration driven by self-interest, where individuals relocate to maximize personal gains, often using heuristic strategies. However, this paper introduces a novel concept: mobility based on fairness rather than self-interest. In this framework, individuals are motivated to move towards environments perceived as fairer, thereby fostering equitable interactions. Fairness-driven mobility has the potential to create cooperative clusters, as like-minded individuals congregate in communities that prioritize justice and fairness. Our simulation results reveal a dual nature of fairness-seeking behavior in cooperative dynamics. On one hand, fairness-seeking can enhance cooperation by establishing stable, supportive clusters that resist exploitation. On the other hand, it can inhibit cooperation by causing frequent relocations and disrupting existing cooperative networks. This duality underscores the complexity of integrating fairness into mobility models and suggests that the impact of fairness on cooperation is highly context-dependent. By exploring this approach, we aim to provide deeper insights into how fairness can shape the evolution of cooperation, complementing traditional models and offering new perspectives on fostering cooperative behavior in structured populations.

2. The model

This study investigates a spatial public goods game (SPGG) [53, 54, 55, 56, 57, 58, 59, 60, 61] on a lattice, incorporating a fairness-driven migration mechanism. The primary objective is to explore how fairness considerations influence the spatial distribution of agents and the overall level of cooperation within the population.

In a standard SPGG, individuals are arranged on the nodes of a square lattice and can choose to either contribute to a common pool (cooperators) or not (defectors). The contributions of cooperators are multiplied by an

enhancement factor r and the resulting total is evenly distributed among all members of the group, regardless of their contribution.

Consider a population arranged on a square lattice of size $L \times L$, where each individual interacts with its k nearest neighbors, creating overlapping groups. Specifically, each player belongs to $k + 1$ groups, with each group comprising the player and their k neighboring individuals.

If a player i is a cooperator, he or she contributes c units to the public good. The total contribution of cooperators in a group g is given by:

$$C_g = \sum_{j \in g} c_j$$

where $c_j = c$ if player j is a cooperator, and $c_j = 0$ if player j is a defector. The payoff for each player i in group g is:

$$P_i^g = \frac{r \cdot C_g}{k + 1} - c_i$$

Each player's total payoff P_i is the sum of the payoffs from all groups they belong to:

$$P_i = \sum_g P_i^g$$

In our model, the population is arranged on a square lattice of size $L \times L$ (L is fixed at 50 in our simulations) with periodic boundary conditions, with a population density $\rho = N/L^2$, where N represents the number of agents, including some empty sites to allow for mobility. Agents interact with their nearest neighbors based on the Von Neumann neighborhood, which includes up to four adjacent neighbors (North, South, East, West). The number of available neighbors k can range from 1 to 4. Isolated agents, without any neighbors, do not participate in the PGG.

At each time step, agents update their states asynchronously in random sequential order. When selected, an agent decides either to move or to update its strategy based on the payoffs from current PGG interactions. The decision-making process is governed by a time scale ratio W ; with probability W , the agent chooses to move, and with probability $1 - W$, it updates its strategy.

If the agent decides to move, it evaluates the environmental fairness of its current site and adjacent empty sites by calculating the variance in payoffs among the agents within the neighborhood of the sites. In this context, a

lower variance indicates higher fairness, as it reflects a more even distribution of payoffs among the agents.

For each potential site (including the current site and any adjacent empty sites), the agent performs the following steps:

1. **Identify Neighboring Agents:** Determine the agents within the Von Neumann neighborhood (North, South, East, West) of each potential site.
2. **Calculate Payoffs:** Compute the payoffs for all neighboring agents (excluding the focal agent) based on the standard rules of the SPGG. For each agent j (excluding the focal agent) within the neighborhood of a potential site s :

$$P_j = \sum_{g \in \mathcal{G}_j} \left(\frac{r \cdot C_g}{k + 1} - c_j \right)$$

Here, \mathcal{G}_j represents the groups to which agent j belongs, C_g is the total contribution in group g , k is the number of neighbors, r is the enhancement factor, and c_j is the contribution of agent j (which is 1 for cooperators and 0 for defectors).

3. **Evaluate Fairness:** Calculate the variance in payoffs among the neighboring agents for each potential site:

$$Variance_s = \frac{1}{n_s} \sum_{j \in \mathcal{N}_s} (P_j - \bar{P}_s)^2$$

where \mathcal{N}_s is the set of neighboring agents at site s , n_s is the number of neighboring agents, and \bar{P}_s is the average payoff of the neighboring agents at site s :

$$\bar{P}_s = \frac{1}{n_s} \sum_{j \in \mathcal{N}_s} P_j$$

4. **Determine the Best Site:** Identify the site with the lowest variance in payoffs, which indicates the highest perceived fairness. If the current site has the lowest variance, the agent remains at its current position. If a neighboring site has a lower variance, the agent moves to that site.

By following this process, agents are more likely to migrate towards environments where the distribution of payoffs is more equitable, thereby promoting movement towards fairer settings. Notably, by excluding the focal agent from the fairness calculation, we ensure that the agent's decision is based purely on the fairness observed among its neighbors. This

approach effectively excludes social preferences such as inequality aversion or envy from influencing the agent’s movement decision. Consequently, the migration mechanism focuses on achieving an objective measure of fairness, allowing for a more accurate assessment of the environmental equity.

Additionally, a probabilistic element is introduced to the agent’s movement. With probability μ , the agent will move to a randomly chosen empty site without considering fairness. This mechanism introduces randomness into the system, reflecting real-world scenarios where agents might move due to various unpredictable factors. This random movement can disrupt existing patterns and prevent the system from becoming overly deterministic, ensuring a diverse range of interactions and potentially promoting a richer set of dynamic behaviors.

When updating its strategy, the agent adheres to the standard SPGG rules. It first calculates the payoffs for itself and its neighboring agents based on their participation in the PGG. The agent then observes the strategies of its neighbors and compares their success. If one of the neighbors has achieved a higher payoff, the agent adopts that neighbor’s strategy. However, if the agent’s own payoff is the highest among its neighbors, no strategy change is made.

The detailed update process for each agent is outlined in Algorithm 1.

Several key parameters influence the dynamics of cooperation and the overall population structure in this model. These include the enhancement factor (r), which determines the benefit multiplier for contributions to the public good; the time scale ratio (W), which governs the balance between movement and strategy updates; the population density (ρ), indicating the proportion of occupied sites on the grid; and the migration noise level (μ), which introduces a probability of random movement irrespective of fairness considerations. By systematically exploring the parameter space, we aim to gain a deeper understanding of how these factors interact to shape the emergence and stability of cooperative behavior. Specifically, we seek to identify conditions under which fairness-driven mobility fosters cooperation, how random movement influences fairness-driven mechanism, and the role of strategic adaptation in maintaining cooperative clusters. This comprehensive analysis will provide insights into the mechanisms underlying social cohesion and the resilience of cooperative networks in structured populations.

Algorithm 1: Update Process of Each Agent

```

1 Procedure UpdateAgent(agenti):
2   Generate a random number  $p$  uniformly distributed in  $[0, 1)$ ;
3   if  $p < W$  then
4     Identify all adjacent empty sites using Von Neumann neighborhood;
5     if  $\{\text{empty adjacent sites}\} \neq \emptyset$  then
6       Generate a random number  $q$  uniformly distributed in  $[0, 1)$ ;
7       if  $q < \mu$  then
8         Move to a randomly selected site from  $\{\text{empty adjacent sites}\}$ ;
9       else
10         $S \leftarrow \{\text{current site}\} \cup \{\text{empty adjacent sites}\}$ ; // define potential
11        Sites include current site and empty adjacent sites
12         $Variance_{min} \leftarrow \infty$ ;
13         $BestSites \leftarrow \emptyset$ ;
14        for each site s in  $S$  do
15          Identify neighboring agents  $\mathcal{N}_s$  at site  $s$  excluding agenti;
16          if  $|\mathcal{N}_s| > 1$  then
17            Calculate payoffs  $P_j$  for each agent  $j \in \mathcal{N}_s$ ;
18            Compute average payoff  $\bar{P}_s = \frac{1}{|\mathcal{N}_s|} \sum_{j \in \mathcal{N}_s} P_j$ ;
19            Calculate variance  $Variance_s = \frac{1}{|\mathcal{N}_s|} \sum_{j \in \mathcal{N}_s} (P_j - \bar{P}_s)^2$ ;
20          else
21             $Variance_s \leftarrow 0$ ; // If only one neighbor, variance is
22            zero
23          if  $Variance_s < Variance_{min}$  then
24             $Variance_{min} \leftarrow Variance_s$ ;
25             $BestSites \leftarrow \{s\}$ ;
26          else
27            if  $Variance_s == Variance_{min}$  then
28               $BestSites \leftarrow BestSites \cup \{s\}$ ;
29        Move to a randomly selected site from  $BestSites$ ;
30      else
31        No Movement Possible; // Maintain current site and strategy
32        End Update Process;
33    else
34      Identify neighboring agents  $\mathcal{N}_i$ ;
35      if  $\mathcal{N}_i \neq \emptyset$  then
36        /* Calculate Payoffs for Neighbors */
37        for each neighbor j in  $\mathcal{N}_i$  do
38          Calculate total payoff  $P_j$  Using SPGG rules
39        Calculate total own payoff  $P_i$ ;
40        Let  $j^* = \arg \max_{j \in \mathcal{N}_i} P_j$ ;
41        if  $P_{j^*} > P_i$  then Adopt the strategy of agent  $j^*$ ;
42      else
43        No Neighbors to Compare; // Maintain current strategy
44        End Update Process;

```

3. Results

In our analysis, we focus on two key measures to evaluate the dynamics of cooperation and the structure of the population: the fraction of cooperators (f_c) and the average group size (G) in all public goods game (PGG) interactions. In our simulations, the final results are obtained from 30-50 independent realizations, after at least 5000 time steps. For each simulation realization, cooperators and defectors are initially distributed in equal proportions. Cooperators, defectors, and empty sites are randomly assigned across the lattice, ensuring a heterogeneous initial configuration.

The fraction of cooperators denotes the proportion of individuals adopting cooperative strategies within the population. This measure is crucial for understanding the overall prevalence of cooperative behavior in the system. A higher fraction indicates that cooperative strategies are more successful and widespread, while a lower fraction suggests that defection is more dominant. When we observe a high fraction of cooperators, it implies that cooperative strategies are being successfully maintained and propagated within the population. This success is likely due to effective fairness-driven migration, which allows cooperators to form stable clusters, thereby enhancing mutual benefits and resilience against defectors. Conversely, a low fraction of cooperators indicates that defectors are more prevalent, potentially undermining cooperative efforts. This scenario could occur if the migration mechanism fails to sufficiently isolate cooperators from defectors or if random movements (μ) introduce too much noise, disrupting cooperative clusters.

The average group size in all PGG interactions represents the typical number of individuals participating in each game, providing insights into the population's connectivity and the effectiveness of cooperative interactions. This measure is crucial for assessing how effectively the migration mechanism fosters a cohesive and cooperative structure within the population. A larger average group size indicates better formation of cooperative clusters, while a smaller size may signal fragmentation and reduced effectiveness of cooperative efforts.

First, it is essential to consider the impact of population density. Population density (ρ) plays a critical role in SPGG with migration and empty sites, as it determines the frequency and intensity of agent interactions. This density significantly influences the formation of cooperative clusters and the overall dynamics of cooperation. High population densities facilitate frequent interactions, which can foster cooperation by enabling cooperators to form robust clusters. Conversely, low densities may result in isolated agents,

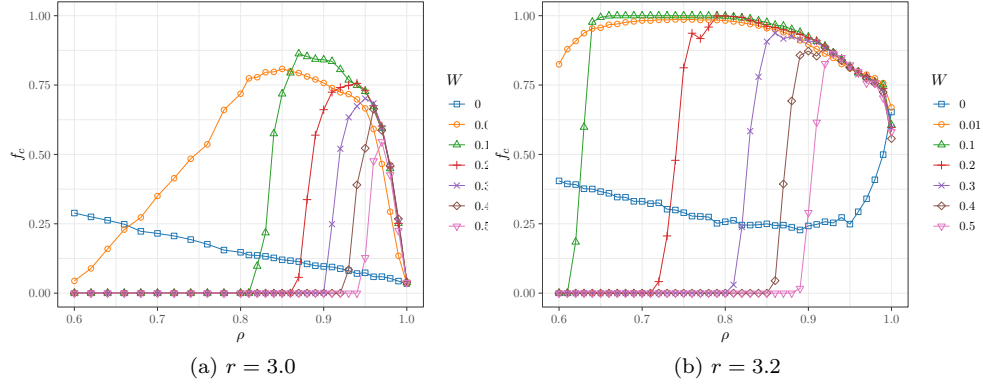


Figure 1: Fraction of cooperators (f_c) as a function of population density (ρ) for various time scale ratios (W) and enhancement factors $r = 3.0$ and $r = 3.2$ in the absence of random movement ($\mu = 0$). For $r = 3.0$, the fraction of cooperators (f_c) steadily decreases with increasing density when there is no movement ($W = 0.0$). Introducing minimal movement ($W = 0.01$) enhances f_c , peaking at around $\rho = 0.85$, while small movements ($W = 0.1$) further boost cooperation, peaking around $\rho = 0.87$. Moderate movements ($W = 0.2$ and $W = 0.3$) continue to support cooperation but with lower peaks. However, with excessive movement ($W \geq 0.4$), cooperative clusters become disrupted, causing f_c to drop significantly across all densities. For $r = 3.2$, f_c initially declines as density increases without movement but rises at very high densities, suggesting stable clusters form even without mobility. Small movements ($W = 0.01$ and $W = 0.1$) lead to near-perfect cooperation around $\rho = 0.7$, maintaining high f_c until $\rho \approx 0.9$. With higher movements ($W \geq 0.2$), cooperation remains high but slightly declines as density increases further. At low population densities, movement reduces cooperation levels compared to the no-movement scenario, implying that frequent interactions between sparse agents inhibit the formation of stable cooperative clusters.

which can hinder the spread of cooperation but also reduce exploitation by defectors. This complex interplay between interaction frequency and cooperative stability suggests the existence of an optimal density where cooperation is maximized, a phenomenon observed in previous studies [62, 63].

Figure 1a illustrates the fraction of cooperators (f_c) as a function of population density (ρ) for varying time scale ratios (W), with two enhancement factors: $r = 3.0$ and $r = 3.2$. Note that in this scenario, $\mu = 0$, meaning there is no random movement.

In the $r = 3.0$ case, without movement ($W = 0.0$), the fraction of cooperators (f_c) steadily decreases as population density increases. This indicates that cooperators are increasingly exploited by defectors in higher density settings. Introducing a very small degree of movement ($W = 0.01$) causes f_c to rise sharply as population density increases, peaking at $\rho \approx 0.85$ with $f_c \approx 0.81$, before declining at higher densities. This suggests that even a

minimal amount of movement enhances the formation of cooperative clusters, although cooperators are still vulnerable at very high densities. For a slightly larger movement probability ($W = 0.1$), the fraction of cooperators follows a similar but slightly more pronounced trend, peaking around $f_c = 0.88$ at $\rho \approx 0.87$ and declining more steeply at higher densities. This indicates that limited movement further facilitates the formation of robust cooperative clusters, but overcrowding at high densities disrupts these clusters. As the movement probability increases to $W = 0.2$ and $W = 0.3$, a similar pattern emerges with peaks at slightly lower fractions of cooperators, near $f_c = 0.75$ and $f_c = 0.65$ respectively, at $\rho \approx 0.95$. This indicates that moderate movement supports the formation of cooperative clusters, but further increases begin to disrupt these clusters before they can fully stabilize. For higher values of W (0.4 and 0.5), the fraction of cooperators remains very low across all densities, as excessive movement prevents the formation of stable cooperative clusters, allowing defectors to overtake cooperators.

In the $r = 3.2$ case, without movement ($W = 0.0$), f_c initially decreases with increasing density but then rises as ρ continues to increase. This suggests that at very high densities, even without movement, cooperators can form stable clusters due to the sheer number of interactions overwhelming defectors' ability to exploit them. Introducing a very small degree of movement ($W = 0.01$) results in a dramatic improvement in cooperation, with f_c quickly rising and reaching nearly 1.0 for $\rho \approx 0.7$. This level of cooperation is sustained up to $\rho \approx 0.9$, after which it sharply declines. The introduction of such minimal movement proves highly effective in stabilizing cooperative clusters across a wide density range, though overcrowding at very high densities disrupts this stability. With a slightly larger movement probability ($W = 0.1$), f_c again rises quickly, reaching close to 1.0 at $\rho \approx 0.6$, and remains high until $\rho \approx 0.9$, after which cooperation declines rapidly. This indicates that limited movement allows cooperators to form highly stable and cohesive clusters, maximizing cooperation across a wide range of densities, but very high densities still disrupt these clusters. As the movement probability increases to $W = 0.2$, f_c rises sharply around $\rho = 0.7$, peaking at $f_c \approx 1$ and maintaining high levels of cooperation up to $\rho \approx 0.9$. With $W = 0.3$, the pattern remains similar, with f_c rising steeply at $\rho \approx 0.8$ and peaking around $f_c = 0.85$. The decline at higher densities is more pronounced, suggesting that increased movement disrupts cooperative clusters more noticeably at higher densities. For $W = 0.4$ and $W = 0.5$, there is a sharp rise in f_c at higher densities. This indicates that even with higher movement probabilities, cooperative clusters can still form at very high densities, though they are less stable and effective compared to lower

W values.

The comparison between the two cases highlights the critical role of the enhancement factor (r) in determining the success of cooperative strategies. At $r = 3.0$, moderate movement is essential for forming and maintaining cooperative clusters, but excessive movement leads to their disruption. At $r = 3.2$, the system exhibits greater resilience, with high levels of cooperation achieved even at higher densities and with more movement.

Another important finding from Figure 1 is that in both cases ($r = 3.0$ and $r = 3.2$), at low population densities, the cooperation level (f_c) with movement can be even lower than in the no movement case ($W = 0.0$), particularly when the enhancement factor r is small. In the no movement case ($W = 0.0$), low density means agents are relatively isolated, and interactions are limited. While this setting reduces the opportunities for cooperators to form large cooperative clusters, it also limits the opportunities for defectors to exploit cooperators. Therefore, the level of cooperation is relatively stable, albeit low. When movement is introduced at low densities, the dynamics change. Low density combined with movement means that agents move frequently but still interact infrequently. This increased isolation can prevent the formation of stable clusters of cooperators. Cooperators might move to find better conditions, but with few neighbors, they fail to form supportive groups. As the agents move around seeking better environments, their efforts are diluted. They are less likely to encounter and cluster with other cooperators, leading to sporadic and weak cooperative interactions. This contrasts with the no movement scenario, where even though cooperators are isolated, their limited interactions are more consistent. In a sparse environment with movement, defectors can easily exploit the transient nature of cooperators. Cooperators moving in search of better conditions often end up encountering defectors, who take advantage of their contributions without reciprocating, thereby lowering the overall cooperation level.

The role of the time scale ratio (W) in the dynamics of cooperation is critical for understanding how different rates of movement and strategy updating impact the formation and stability of cooperative clusters. By examining the time scale ratio, we can gain insights into the optimal balance between movement and strategy adaptation that fosters cooperation in SPGG. Figure 2 illustrates the fraction of cooperators (f_c) as a function of the time scale ratio (W) for various enhancement factors (r) and population densities (ρ) in the absence of random movement ($\mu = 0$). Different lines represent various enhancement factors (r), ranging from 2.8 to 4.0. For $r = 2.8$, the fraction of cooperators remains very low across all W values, indicating that this enhancement factor is insufficient to sustain coopera-

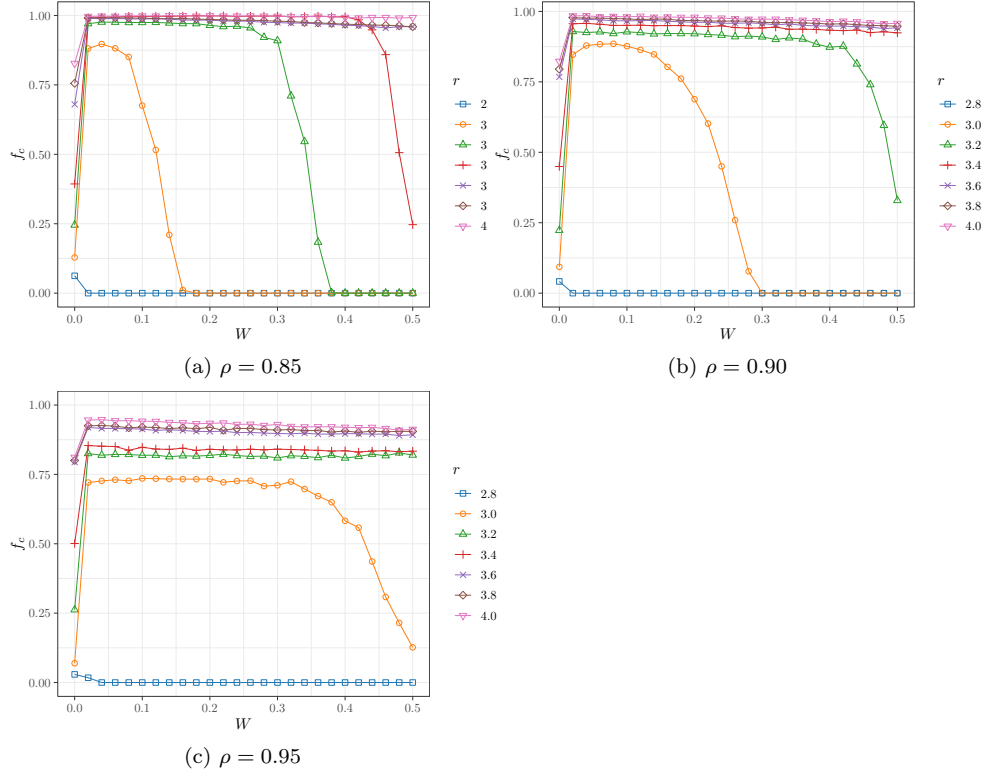


Figure 2: Impact of time scale ratio (W) on the fraction of cooperators (f_c) for different enhancement factors (r) and population densities (ρ) in the absence of random movement ($\mu = 0$). The time scale ratio (W) critically influences the dynamics of cooperation, affecting how movement and strategy updates shape cooperative clusters. At $\rho = 0.85$, f_c remains low for $r = 2.8$ across all W values. For $r = 3.0$, f_c peaks at low W but declines with higher W . For $r = 3.2$ and higher, f_c stays near 1.0 across most W values, with only slight declines at very high W . At $\rho = 0.90$, the trends are similar. For $r = 3.0$, f_c peaks at moderate W before declining. For $r = 3.2$ and higher, f_c remains high across all W values, showing strong resilience to movement. At $\rho = 0.95$, f_c is consistently low for $r = 2.8$. For $r = 3.0$, moderate W values support cooperation, but higher W disrupts it. For $r = 3.2$ and higher, f_c remains robust. Higher population density provides a wider range of W for supporting cooperation but can lower the highest achievable f_c . High density limits fairness-seeking movement due to fewer empty sites, rebalancing movement intensity to moderate levels. This also increases opportunities for defectors to exploit cooperators, lowering the highest possible cooperation level for various r values.

tion. For $r = 3.0$, f_c increases sharply at low W values and remains high up to $W \approx 0.1$, after which it declines, suggesting that moderate movement promotes cooperation, but excessive movement disrupts it. For $r = 3.2$ and $r = 3.4$, f_c quickly reaches near 1.0 and stays high across most W values, in-

dicating robust cooperation, with slight declines only at very high W values. For $r = 3.6$, $r = 3.8$, and $r = 4.0$, the fraction of cooperators remains consistently high across all W values, demonstrating that very high enhancement factors provide a strong buffer against the disruptive effects of movement. Notably, the decline in f_c for $r = 3.2$ starts around $W = 0.25$, while for $r = 3.4$ it begins around $W = 0.4$, indicating that higher enhancement factors not only support higher initial cooperation but also extend the range of W over which high cooperation levels are maintained.

For a population density of $\rho = 0.90$ (Figure 2b), the trends align closely with those observed at $\rho = 0.85$. For $r = 2.8$, the fraction of cooperators (f_c) remains low across all W values, underscoring the insufficiency of this enhancement factor to support cooperation. For $r = 3.0$, f_c peaks at moderate W values before declining, indicating that while moderate movement can foster cooperation, excessive movement undermines it. When $r = 3.2$, f_c rises sharply to near 1.0 at low W values and starts to decline at $W \approx 0.4$, highlighting the threshold at which movement becomes detrimental to cooperation. For higher values of r (3.4 and above), f_c maintains high levels across all W values, showing that strong enhancement factors sustain cooperation even with increasing movement.

For a population density of $\rho = 0.95$ (Figure 2c), the pattern for $r = 2.8$ remains consistent with previous observations, with f_c staying low across all W values, indicating that this enhancement factor is insufficient to sustain cooperation. For $r = 3.0$, f_c peaks at moderate W values and declines at higher W , suggesting that while moderate movement can foster cooperation, excessive movement disrupts it. For $r = 3.2$ and higher, f_c remains robust across all W values, demonstrating a high level of cooperation.

These findings are consistent with our previous research on the effect of population density (ρ) on cooperation. Both studies highlight that moderate movement generally promotes cooperation by facilitating the formation of cooperative clusters, while excessive movement can disrupt these clusters. Higher enhancement factors (r) not only support higher initial cooperation but also extend the range of W over which high cooperation levels are maintained, providing a buffer against the disruptive effects of movement. This reinforces the importance of balancing movement and strategy adaptation to sustain cooperation in structured populations.

Additionally, by comparison, we observe that higher population density (ρ) provides a wider range of W for supporting cooperation but may lower the highest achievable level of cooperation for different r values. With high density, there are fewer empty sites, making fairness-seeking movement less feasible because agents have fewer opportunities to find new sites to move

to. Therefore, not only the time scale parameter W , but also the population density controls how often movement occurs. In systems with high density, the realized movement intensity is naturally rebalanced to be more moderate under high W . However, high density also leads to higher connectivity, which can provide opportunities for defectors to exploit cooperators, thereby lowering the highest possible cooperation level for different r values.

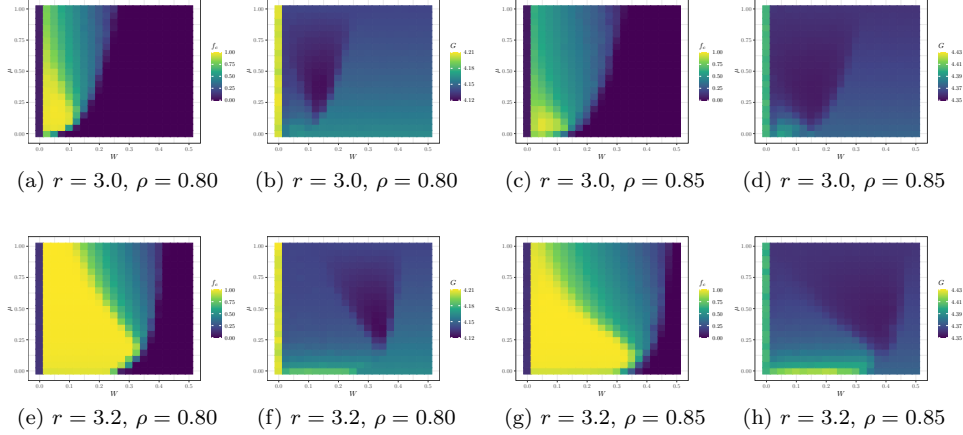


Figure 3: Impact of time scale ratio (W) and movement noise (μ) on cooperation and group dynamics. For $r = 3.0$ and $r = 3.2$ across population densities $\rho = 0.80$ and $\rho = 0.85$, cooperation (f_c) is highest with low to moderate W and μ . Higher noise levels broaden the range of W values that support cooperators but lead to a mix of cooperators and defectors. Average group size (G) is lowest at moderate W and μ , with very high noise reducing the impact of fairness-seeking movement, thus increasing G in moderate W ranges. Higher density ($\rho = 0.85$) shows larger coexistence ranges for cooperators and defectors, and lower G due to fewer empty sites, which limits fairness-seeking movement. Increased density enhances interactions but also benefits defectors, reducing overall cooperation levels. Overall, moderate noise supports cooperator survival but lowers high cooperation levels, necessitating a balance of movement and noise to sustain cooperation and stable group structures.

Figure 3 provides a comprehensive examination of how the time scale ratio (W) and noise in movement (μ) influence cooperation and group dynamics within a population. For $r = 3.0$ and $r = 3.2$, across two population densities ($\rho = 0.80$ and $\rho = 0.85$), the fraction of cooperators (f_c) and the average group size (G) reveal intricate patterns.

Figure 3a and Figure 3c illustrate the fraction of cooperators for $r = 3.0$. The highest levels of cooperation are achieved when both W and μ are low to moderate, suggesting that minimal movement and noise facilitate the formation of cooperative clusters. As μ increases, the range of W values that

support the survival of cooperators broadens. However, higher noise levels result in a mix of cooperators and defectors, with diminished fairness-seeking mechanisms giving way to dynamics driven by random movement. Figure 3e and Figure 3g, depicting $r = 3.2$, show an enlarged range of high cooperation compared to lower r values. High cooperation levels are maintained across a broader range of W and μ values, indicating greater resilience of cooperative behavior under varied movement and noise levels. There is an optimal μ that maximizes the range of W values supporting high cooperation, facilitating a balance between movement and strategy adaptation and enabling cooperators to form stable clusters more effectively. Figure 3b and Figure 3d highlight the average group size for $r = 3.0$. The lowest group sizes are observed when both W and μ are moderate, explained by the coexistence of cooperators and defectors, resulting in lower fairness and more fairness-seeking movement. As μ increases, group size initially decreases, suggesting that moderate noise disrupts group stability. However, very high μ increases average group size in the moderate W range, indicating that excessive noise reduces the impact of fairness-seeking movement. Figure 3f and Figure 3b, for $r = 3.2$, reveal that the largest group sizes occur at $\mu = 0$ and low W values, indicating that minimal noise and movement facilitate the formation of large, stable groups. As μ increases, group size initially decreases, suggesting that even moderate noise disrupts group stability. However, very high noise levels increases average group size, leading to larger average group sizes overall.

The patterns observed underscore the importance of noise in movement. Moderate noise (μ) broadens the conditions under which cooperators can survive but does not necessarily support high cooperation levels. Instead, it facilitates a dynamic balance where both cooperators and defectors can persist. The stability and size of cooperative groups are disrupted when both movement and noise are moderate, leading to environments where mixed strategies result in smaller groups. Excessive noise undermines fairness-seeking behaviors, leading to fragmented group structures but can also stabilize group sizes in moderate W ranges by reducing fairness-seeking movement.

In higher population density scenarios ($\rho = 0.85$), the range of coexistence of cooperators and defectors is larger than in the lower density case ($\rho = 0.80$). Additionally, the range of low average group sizes (G) is more extensive in higher density environments. This phenomenon can be attributed to the reduced availability of empty sites in denser populations, limiting the effectiveness of fairness-seeking movement. Agents have fewer opportunities to relocate to new sites, which moderates the intensity of movement

driven by fairness considerations. Consequently, the migration mechanism is inherently rebalanced in high-density settings.

This rebalancing has dual effects: it promotes coexistence by providing survival chances for cooperators amidst defectors, but it also lowers the highest possible cooperation levels. The increased interaction opportunities in denser populations enhance connectivity among agents, which can benefit defectors and reduce overall cooperation levels. Thus, both the time scale parameter W and population density ρ play crucial roles in controlling movement frequency and the resultant cooperative dynamics.

The effect of population density on cooperation also varies with different noise levels (μ). When μ is low, higher population density can enlarge the range of W values that support high cooperation, consistent with our previous analyses (Figure 2). However, when μ is high, the range of highest cooperation is limited by the broader mixed range of coexistence between cooperators and defectors. This indicates that the interplay between density and noise significantly influences the cooperative landscape, with density moderating the frequency and impact of fairness-seeking movement.

The figures illustrate the complex dynamics between W and μ in SPGG, emphasizing the delicate balance required to sustain cooperation. Moderate noise enhances the survival of cooperators but lowers the potential for high cooperation levels, leading to a dynamic balance between cooperators and defectors. In higher population densities, the range of coexistence broadens, and the low group size range extends due to the reduced impact of fairness-seeking movement. Understanding the interplay between movement, noise, and density is crucial for fostering cooperative behavior and maintaining stable social structures in complex populations.

Next, we will explore the spatial structure of the system to gain deeper insights into the fairness-seeking mechanism and its impact on cooperation. Examining the spatial distribution of cooperators, defectors, and empty sites over time allows us to understand how different time scale ratios (W) and population densities (ρ) influence the formation and stability of cooperative clusters. This analysis is crucial as it reveals the underlying dynamics that drive the evolution of cooperation and defection, providing a clearer picture of how movement and density interact to shape social behavior in structured populations.

Figure 4 offer a detailed view of the system's evolution under varying parameters of W and ρ . These snapshots depict cooperators (red), defectors (blue), and empty sites (white) as they change over time across four distinct scenarios: $W = 0.1, \rho = 0.85$; $W = 0.2, \rho = 0.85$; $W = 0.1, \rho = 0.9$; and $W = 0.2, \rho = 0.9$. By analyzing these spatial patterns, we can better under-

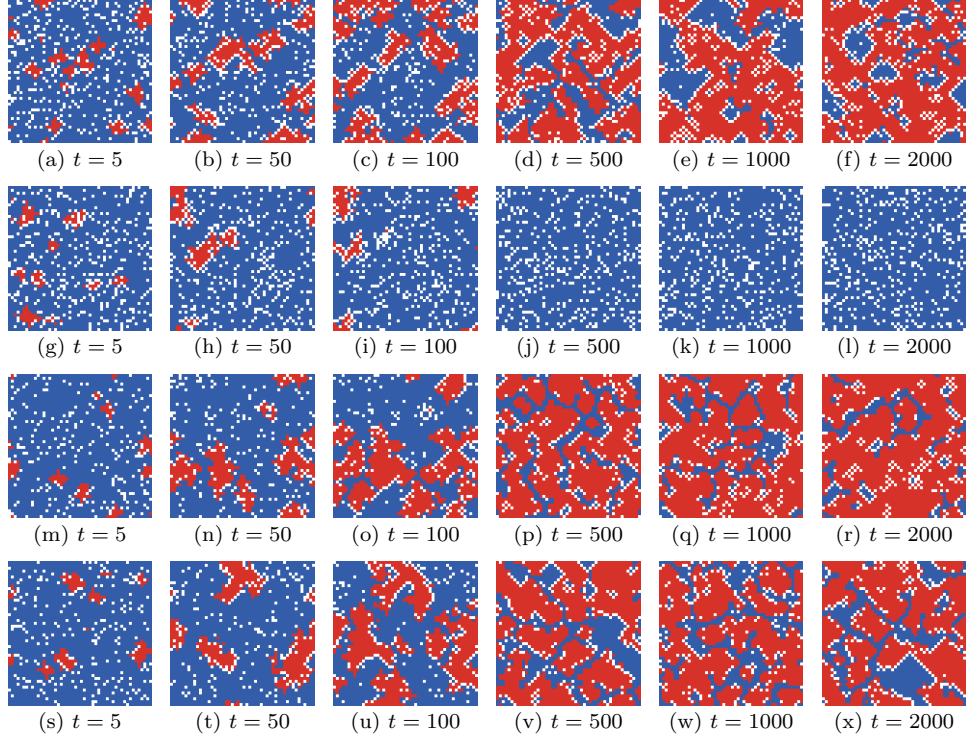


Figure 4: Evolution of spatial structures under different time scale ratios (W) and population densities (ρ). The snapshots depict cooperators (red), defectors (blue), and empty sites (white) over time for four scenarios: $W = 0.1$, $\rho = 0.85$ ((a)-(f)); $W = 0.2$, $\rho = 0.85$ ((g)-(l)); $W = 0.1$, $\rho = 0.9$ ((m)-(u)); and $W = 0.2$, $\rho = 0.9$ ((s)-(x)). At $W = 0.1$ and $\rho = 0.85$, cooperative clusters form and stabilize over time, as cooperators are allowed to expand. At $W = 0.2$ and $\rho = 0.85$, higher movement rates cause empty sites to quickly encircle cooperators, inhibiting their expansion and allowing defectors to infiltrate. With $\rho = 0.9$ and $W = 0.1$, cooperative clusters expand significantly, leading to robust cooperation. At $W = 0.2$ and $\rho = 0.9$, cooperative clusters face more infiltration by defectors, resulting in less stable yet significant cooperation. The distribution of empty sites plays a crucial role in these dynamics, influencing the expansion and stability of cooperative clusters.

stand how the fairness-seeking mechanism, combined with different rates of movement and population densities, affects the emergence and maintenance of cooperative behavior.

At $W = 0.1$ and a population density of $\rho = 0.85$ (Figures 4a to 4f), small cooperative clusters start to form by $t = 5$, interspersed with defectors and empty sites. By $t = 50$, these clusters become more pronounced, though defectors still occupy significant portions of the lattice. By $t = 100$, larger

cooperative clusters form, pushing defectors. At $t = 500$, these clusters become more distinct, with cooperators forming stable regions while defectors are increasingly marginalized. By $t = 1000$ and $t = 2000$, cooperative clusters dominate, demonstrating the effectiveness of low movement rates in fostering stable cooperative behavior in moderately dense populations. In the scenario with $W = 0.2$ and $\rho = 0.85$ (Figures 4g to 4l), small cooperative clusters also begin to form by $t = 5$. By $t = 50$, cooperative clusters are less distinct due to the higher movement rate, allowing defectors to infiltrate these clusters more easily. At $t = 100$, clusters struggle to stabilize, with defectors interspersed among cooperators. By $t = 500$, cooperative clusters start to diminish. By $t = 1000$ and $t = 2000$, defectors dominate, leading to the disappearance of cooperators. When the population density is increased to $\rho = 0.9$ with $W = 0.1$ (Figures 4m to 4r), small cooperative clusters form by $t = 5$, interspersed with defectors and empty sites. By $t = 50$, these clusters expand significantly. By $t = 100$, cooperative regions begin to dominate, pushing defectors into smaller pockets. At $t = 500$, cooperative regions dominate even more. By $t = 1000$ and $t = 2000$, cooperation remains robust, with large, stable cooperative clusters clearly visible. At $W = 0.2$ and $\rho = 0.9$ (Figures 4s to 4x), small cooperative clusters also start forming by $t = 5$. By $t = 50$, the clusters grow but face more infiltration by defectors. By $t = 100$, cooperative clusters expand, but defectors are more evenly spread among them. By $t = 500$, cooperative clusters remain robust despite some defector presence. By $t = 1000$ and $t = 2000$, large cooperative regions are maintained, but the clusters show more instability compared to the lower W scenario.

Examining these four cases reveals key differences influenced by the time scale ratio (W) and population density (ρ). At $W = 0.1$ and $\rho = 0.85$, small cooperative clusters form early and become more pronounced, with stable cooperative regions emerging over time as defectors are marginalized. Conversely, at $W = 0.2$ and $\rho = 0.85$, higher movement rates disrupt these clusters, resulting in a struggle to stabilize and eventual domination by defectors. Increasing the population density to $\rho = 0.9$ with $W = 0.1$ sees early cooperative clusters expanding significantly, leading to robust, stable cooperation over time. However, at $W = 0.2$ and $\rho = 0.9$, cooperative clusters still form early but face more infiltration by defectors, leading to less stable yet still significant cooperative regions.

We can explain the differences in the four cases by focusing on the role of empty sites. The spatial distribution of empty sites is crucial for understanding the dynamics of cooperation and defection. These empty sites can serve as defensive barriers, preventing defectors from exploiting cooperators,

but they can also inhibit the expansion of cooperators if they fully encircle them. An optimal structure would have empty sites forming walls that separate cooperators and defectors, while still allowing cooperators to expand into defector areas. By examining how empty sites form walls and gaps, we can gain insights into how different time scale ratios (W) and population densities (ρ) influence the formation and stability of cooperative clusters. This analysis reveals the underlying mechanisms that drive the evolution of cooperation and defection, providing a clearer picture of how spatial structures shape social behavior in structured populations.

At $W = 0.1$, the empty sites do not move quickly enough to fully encircle cooperators, leaving space for their expansion. This allows cooperative clusters to grow and stabilize over time, as seen in Figures 4a to 4c. Conversely, at $W = 0.2$, empty sites quickly surround cooperators, preventing their expansion and leaving them vulnerable to defector infiltration, as shown in Figures 4g to 4i. The higher movement rate results in cooperators being almost fully encircled by empty sites, inhibiting the growth of cooperative clusters and allowing defectors to disrupt them. Therefore, too frequent movement driven by the fairness-seeking mechanism can inhibit the evolution of cooperation in the early stages.

In the later stages, the time scale ratio (W) continues to play a critical role in the spatial dynamics of cooperation and defection. At a lower W (as shown in Figures 4d to 4f), defectors are progressively marginalized and encircled in smaller areas by cooperative clusters. This spatial structure becomes favorable for cooperators because the encircled defectors have limited opportunities to exploit them. The containment of defectors within small, isolated pockets prevents them from disrupting the larger cooperative regions. This encirclement mechanism results in a positive feedback loop where the stability of cooperative clusters is maintained and reinforced over time. The low W setting creates an environment where cooperators can dominate and sustain their presence, fostering both the evolution and maintenance of cooperation. The reduced mobility ensures that cooperative regions remain robust, and defectors are unable to penetrate these clusters effectively. Thus, a low (W) is beneficial in establishing a spatial structure that not only promotes the growth of cooperative clusters but also ensures their long-term stability by isolating defectors and minimizing their impact.

The perspective of empty sites also helps understand how population density (ρ) affects the evolution of cooperation. In the early stage for both $W = 0.1$ and $W = 0.2$ with $\rho = 0.9$, the number of empty sites is two-thirds of the case with $\rho = 0.85$. This reduction in empty sites significantly influences the spatial structure and dynamics. For both W values (Figures 4m

to 4o and Figures 4s to 4u), the decreased number of empty sites means that cooperative clusters have fewer barriers and more opportunities to expand into defector-dominated regions. This optimal structure allows cooperators to avoid immediate exploitation while maintaining opportunities to expand into defector areas. Consequently, larger cooperative clusters can form more effectively in higher-density scenarios. Thus, even with the higher movement rate ($W = 0.2$), cooperators benefit from the increased density as the limited empty sites create favorable conditions for the establishment and maintenance of large cooperative clusters. This interplay between density and empty sites highlights the critical role of spatial structure in the dynamics of cooperation and defection.

In the later stages, where high cooperation levels are established, the structure in high-density scenarios ($\rho = 0.9$) differs from the low-density cases. Because there are fewer empty sites, the remaining defectors cannot be fully encircled by empty sites but instead survive in narrow strip structures. As defectors attempt to expand, their expansion is quickly limited by walls of empty sites, as illustrated in Figures 4v to 4x. This dynamic creates a different mechanism for maintaining cooperation compared to low-density scenarios. Despite the difference, this mechanism remains effective in supporting the persistence of cooperative behavior, demonstrating how spatial structure and density interplay to sustain cooperation.

Figure 5 offers a comparative analysis of the system's evolution with the inclusion of random movement ($\mu = 0.2$), highlighting its impact on the spatial distribution of cooperators, defectors, and empty sites under different time scale ratios (W) with a population density of $\rho = 0.85$. When random movement is included, the structure of empty sites becomes less wall-like and more irregular. This change means that the encirclement of cooperators by empty sites is less likely to happen. This shift in the spatial structure can have favorable effects, as it provides cooperative clusters with the opportunity to avoid exploitation by defectors and to expand more efficiently. In scenarios with a higher time scale ratio ($W = 0.2$), this effect is particularly pronounced. Without random noise, cooperators are easily encircled by empty sites, which prevents them from expanding and leaves them vulnerable to defector infiltration (as shown in Figures 4g to 4l). However, when random noise in movement ($\mu = 0.2$) is introduced (Figures 5g to 5l), the surrounding empty sites become more dispersed and irregular. This disruption creates a more open and optimal environment for cooperators to expand, mitigating the restrictive effects of higher movement rates. Thus, a combination of a small fairness-seeking time scale with a small amount of random noise might represent an optimal scenario for fostering coopera-

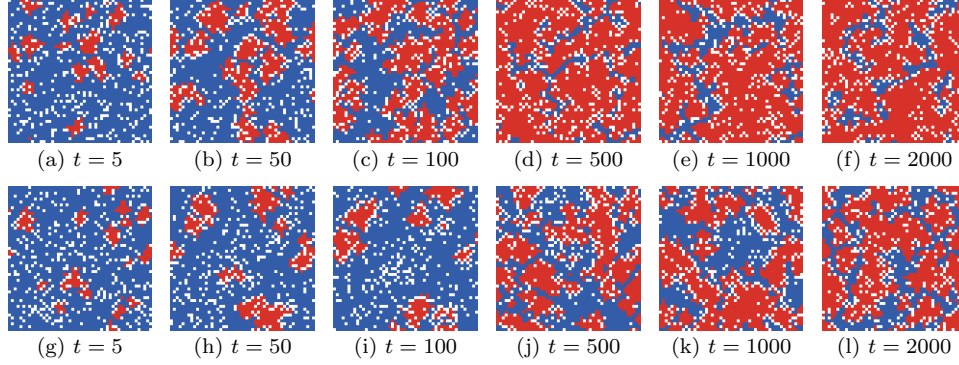


Figure 5: Evolution of spatial structures with the inclusion of random movement ($\mu = 0.2$) under different time scale ratios (W) with a population density of $\rho = 0.85$. The snapshots depict cooperators (red), defectors (blue), and empty sites (white) over time for two scenarios: $W = 0.1$, ((a)-(f)); $W = 0.2$, ((g)-(l)). Random movement disrupts the wall-like structure of empty sites, reducing the likelihood of cooperators being encircled and enhancing their ability to expand. Cooperators benefit significantly from random noise, as it prevents them from being trapped by empty sites, allowing more efficient cluster growth. A small fairness-seeking time scale combined with random noise fosters optimal conditions for cooperation.

tion. This balance allows cooperators to leverage the protective benefits of empty sites without becoming trapped, promoting both the formation and expansion of cooperative clusters.

4. Discussion and Conclusion

The interplay between mobility, fairness, and cooperation has profound implications for understanding the dynamics of cooperative behavior in structured populations. Our study integrates a fairness-driven migration mechanism into a SPGG, revealing how different rates of movement, population densities, and the inclusion of random movement influence the formation and stability of cooperative clusters.

Previous studies have examined how migration influences cooperation in various social dilemmas. For example, risk-driven migration was explored in the context of the collective-risk dilemma, where individuals migrating away from unfavorable conditions significantly improved cooperation levels [38]. Mobility in the voluntary Prisoner's Dilemma restores cooperation by allowing agents to move and form cooperative clusters, reducing exploitation by defectors [39]. Additionally, orientation-driven migration was investigated, revealing that individuals escaping from defectors formed stable cooperative

clusters that better supported cooperation compared to movement toward cooperators [40].

While these studies underscore the importance of migration in promoting cooperation, our research introduces a novel dimension by focusing on fairness-driven migration. Unlike the risk-averse or utility-based migration mechanisms highlighted in prior work, fairness-driven migration incentivizes individuals to relocate toward environments characterized by equitable payoff distributions, rather than simply avoiding unfavorable conditions or defectors. This shift in focus emphasizes the pursuit of fairness as a driver of mobility, which leads to more balanced and stable cooperative interactions. Our findings reveal that fairness-driven migration plays a pivotal role in cultivating cooperation, especially in structured populations where individual movement and strategy updates are simultaneously in effect.

One of the key findings of our research is the critical role of movement in shaping cooperative dynamics. Moderate movement rates promote the formation of cooperative clusters by enabling cooperators to aggregate and form resilient groups. These clusters are essential for maintaining high levels of cooperation, as they provide mutual benefits and protect cooperators from being exploited by defectors. However, excessive movement disrupts these clusters, leading to the dominance of defectors and a decline in overall cooperation. This disruption occurs because high movement rates prevent the stabilization of cooperative groups, causing cooperators to be frequently encircled by empty sites and infiltrated by defectors.

Population density also plays a crucial role in determining the dynamics of cooperation. Higher densities facilitate frequent interactions among agents, promoting the formation of cooperative clusters. However, too high densities can lead to overcrowding, which disrupts these clusters and allows defectors to exploit cooperators more effectively. Our results suggest an optimal density range where cooperation is maximized, balancing the frequency of interactions with the stability of cooperative groups. When density does not exceed the optimal range, the higher density reduces the number of empty sites, altering their spatial distribution around cooperators. This reduction in empty sites creates more opportunities for cooperative clusters to expand and stabilize, as empty sites serve as barriers preventing defectors from infiltrating these clusters. However, beyond this optimal density, overcrowding occurs, and the cooperative clusters are disrupted, diminishing the overall levels of cooperation.

The inclusion of random movement introduces an additional layer of complexity to the dynamics of cooperation. Moderate levels of random movement broaden the conditions under which cooperators can survive, cre-

ating a dynamic balance between cooperators and defectors. This balance is achieved by preventing the encirclement of cooperators by empty sites, allowing for more efficient expansion and maintenance of cooperative clusters. Random movement disrupts the formation of wall-like structures of empty sites, enhancing the ability of cooperators to avoid exploitation and form robust groups.

Our spatial analysis reveals the critical impact of empty sites on cooperative dynamics. In scenarios with low movement rates, empty sites serve as defensive barriers, preventing defectors from exploiting cooperators and allowing cooperative clusters to stabilize and expand. Conversely, higher movement rates lead to the encirclement of cooperators by empty sites, inhibiting their expansion and allowing defectors to infiltrate. The distribution and movement of empty sites are therefore crucial for understanding the spatial dynamics of cooperation and defection.

The findings have broad implications for various fields, including evolutionary biology, sociology, and artificial intelligence. By elucidating the mechanisms underlying the evolution of cooperation, our research provides insights into the factors that promote social cohesion and collective action. The integration of fairness-driven mobility into models of cooperation can inform strategies for enhancing cooperative behavior in human societies, addressing contemporary challenges such as resource distribution, conflict resolution, and climate change mitigation.

In conclusion, our study demonstrates that the evolution of cooperation is intricately linked to the dynamics of movement, fairness, and spatial structure. Moderate movement rates, higher enhancement factors, and the inclusion of random movement create favorable conditions for the formation and maintenance of cooperative clusters. These findings highlight the importance of balancing movement and strategy adaptation to sustain cooperation in structured populations. Understanding the interplay between these factors is crucial for fostering cooperative behavior and maintaining stable social structures in complex populations.

Future research should further explore the nuances of these interactions. One potential avenue is investigating the impact of heterogeneous populations where agents have varying levels of mobility and different sensitivity to fairness. This could provide insights into how diversity in movement and fairness perception influences overall cooperation dynamics. Additionally, studying the effects of dynamic environments, where the population density and resource availability change over time, can shed light on how flexible cooperative strategies adapt to fluctuating conditions. Another interesting direction is to examine the role of communication and information shar-

ing among agents. Introducing mechanisms for agents to share information about the fairness of their local environment and the presence of cooperators and defectors could lead to more sophisticated models of cooperative behavior. This could also involve the integration of learning algorithms, where agents adapt their strategies based on past experiences and shared information. Exploring the implications of our findings for human societies, particularly in digital and online environments, can provide practical applications for enhancing cooperation in virtual communities. Investigating how digital platforms can be designed to promote fairness and cooperation through mobility and interaction mechanisms could offer valuable insights for building more cohesive and collaborative online spaces. Finally, expanding our model to incorporate multi-layered networks, where agents interact across different social and environmental layers, can provide a more comprehensive understanding of cooperation in complex systems. This approach can reveal how interactions in one layer influence behaviors in another, leading to a deeper understanding of the interconnectedness of social and environmental factors in shaping cooperative dynamics.

By pursuing these research directions, we can continue to advance our understanding of the evolution of cooperation and develop strategies to foster cooperative behavior in diverse and complex populations.

References

- [1] E. O. Wilson, *Sociobiology: The new synthesis*, Harvard University Press, 2000.
- [2] E. Fehr, S. Gächter, Cooperation and punishment in public goods experiments, *American Economic Review* 90 (4) (2000) 980–994.
- [3] S. Bowles, H. Gintis, *A cooperative species*, Princeton University Press, 2011.
- [4] R. Bouffanais, *A Biologically Inspired Approach to Collective Behaviors*, Springer Singapore, Singapore, 2016, pp. 5–15. doi:10.1007/978-981-287-751-2_2.
- [5] J. Henrich, Cultural transmission and the diffusion of innovations: Adoption dynamics indicate that biased cultural transmission is the predominate force in behavioral change, *American Anthropologist* 103 (4) (2001) 992–1013.

- [6] P. J. Richerson, R. Boyd, Not by genes alone: How culture transformed human evolution, University of Chicago press, 2008.
- [7] M. Chudek, J. Henrich, Culture–gene coevolution, norm-psychology and the emergence of human prosociality, Trends in cognitive sciences 15 (5) (2011) 218–226.
- [8] B. R. House, J. B. Silk, K. McAuliffe, No strong evidence for universal gender differences in the development of cooperative behaviour across societies, Philosophical Transactions of the Royal Society B (2022). doi:10.1098/rstb.2021.0439.
- [9] A. B. Yaroslavtsev, How to promote cooperation for the well-being of individuals and societies (2023). doi:10.31234/osf.io/gtuj4.
- [10] N. P. Kristensen, H. Ohtsuki, R. A. Chisholm, Ancestral social environments plus nonlinear benefits can explain cooperation in human societies (2022). doi:10.21203/rs.3.rs-1868476/v1.
- [11] J. Wang, How to promote cooperation for the well-being of individuals and societies, Springer series in design and innovation (2023). doi:10.1007/978-3-031-28390-1_2.
- [12] D. G. Rand, M. A. Nowak, Human cooperation, Trends in cognitive sciences 17 (8) (2013) 413–425.
- [13] A. Szolnoki, M. Perc, Emergence of multilevel selection in the prisoner’s dilemma game on coevolving random networks, New Journal of Physics 11 (9) (2009) 093033.
- [14] A. Szolnoki, M. Perc, Resolving social dilemmas on evolving random networks, Europhysics letters 86 (3) (2009) 30007.
- [15] M. Perc, A. Szolnoki, Coevolutionary games—a mini review, BioSystems 99 (2) (2010) 109–125.
- [16] M. Perc, J. J. Jordan, D. G. Rand, Z. Wang, S. Boccaletti, A. Szolnoki, Statistical physics of human cooperation, Physics Reports 687 (2017) 1–51.
- [17] M. A. Nowak, Five rules for the evolution of cooperation, science 314 (5805) (2006) 1560–1563.
- [18] W. D. Hamilton, The evolution of altruistic behavior, The American Naturalist 97 (896) (1963) 354–356.

- [19] J. M. Smith, Group selection and kin selection, *Nature* 201 (4924) (1964) 1145–1147.
- [20] R. Axelrod, The evolution of strategies in the iterated prisoner’s dilemma, *Genetic algorithms and simulated annealing* (1989) 32–41.
- [21] L. Schmid, C. Hilbe, K. Chatterjee, M. A. Nowak, Direct reciprocity between individuals that use different strategy spaces, *PLOS Computational Biology* 18 (6) (2022) e1010149. doi:10.1371/journal.pcbi.1010149.
- [22] M. Van Veelen, J. García, D. G. Rand, M. A. Nowak, Direct reciprocity in structured populations, *Proceedings of the National Academy of Sciences of the United States of America* 109 (25) (2012) 9929–9934. doi:10.1073/PNAS.1206694109.
- [23] M. A. Nowak, K. Sigmund, Evolution of indirect reciprocity by image scoring, *Nature* 393 (6685) (1998) 573–577.
- [24] L. Xiao, W. S. Lin, Y. Chen, K. J. R. Liu, Indirect reciprocity game modelling for secure wireless networks, in: *International Conference on Communications*, 2012. doi:10.1109/ICC.2012.6364034.
- [25] W. Ghang, J. Olejarz, M. A. Nowak, Indirect reciprocity with optional games and monitoring of interactions between defectors, *Mathematical Biosciences* 310 (2019) 108–119.
- [26] M. A. Nowak, R. M. May, Evolutionary games and spatial chaos, *Nature* 359 (6398) (1992) 826–829.
- [27] Z. Wang, S. Kokubo, J. Tanimoto, E. Fukuda, K. Shigaki, Insight into the so-called spatial reciprocity, *Physical Review E* 88 (4) (2013) 042145.
- [28] W.-J. Li, Z. Chen, J. Wang, L.-L. Jiang, M. Perc, Social mobility and network reciprocity shape cooperation in collaborative networks, *Chaos, Solitons & Fractals* 165 (2023) 113378. doi:10.1016/j.chaos.2023.113378.
- [29] Z.-Q. Jiang, P. Wang, J.-C. Ma, P. Zhu, Z. Han, B. Podobnik, H. E. Stanley, W.-X. Zhou, K. Alfaro-Bittner, S. Boccaletti, Unraveling the effects of network, direct and indirect reciprocity in online societies, *Chaos, Solitons & Fractals* 165 (2023) 113276. doi:10.1016/j.chaos.2023.113276.

- [30] J. Wang, W. Xu, W. Chen, F. Yu, J. He, Inter-group selection of strategy promotes cooperation in public goods game, *Physica A: Statistical Mechanics and Its Applications* 579 (2021) 126292. doi:10.1016/J.PHYSA.2021.126292.
- [31] D. R. Smith, Cultural group selection and human cooperation: a conceptual and empirical review (2020). doi:10.1017/EHS.2020.2.
- [32] J. P. Neal, The evolutionary origins of cooperation in the hominin lineage: A critique of boyd and richerson’s cultural group selection account, *Philosophy of Science* 88 (4) (2021) 693–704. doi:10.1086/715221.
- [33] R. Boyd, P. J. Richerson, Culture and the evolutionary process, *The Condor* 88 (1) (1986) 123–. doi:10.2307/1367778.
- [34] D. S. Wilson, L. A. Dugatkin, Group selection and assortative interactions, *The American Naturalist* 149 (2) (1997) 336–351.
- [35] S. Meloni, A. Buscarino, L. Fortuna, M. Frasca, J. Gómez-Gardeñes, V. Latora, Y. Moreno, Effects of mobility in a population of prisoner’s dilemma players, *Physical Review E* 79 (6) (2009) 067101.
- [36] D. Helbing, W. Yu, The outbreak of cooperation among success-driven individuals under noisy conditions, *Proceedings of the National Academy of Sciences* 106 (10) (2009) 3680–3685.
- [37] S. Xiao, L. Zhang, H. Li, Q. Dai, J. Yang, Environment-driven migration enhances cooperation in evolutionary public goods games, *The European Physical Journal B* 95 (4) (2022) 67.
- [38] X. Chen, A. Szolnoki, M. Perc, Risk-driven migration and the collective-risk social dilemma, *Physical Review E—Statistical, Nonlinear, and Soft Matter Physics* 86 (3) (2012) 036101.
- [39] M. Cardinot, C. O’Riordan, J. Griffith, A. Szolnoki, Mobility restores the mechanism which supports cooperation in the voluntary prisoner’s dilemma game, *New Journal of Physics* 21 (7) (2019) 073038.
- [40] Z. Xiao, X. Chen, A. Szolnoki, Leaving bads provides better outcome than approaching goods in a social dilemma, *New Journal of Physics* 22 (2) (2020) 023012.

- [41] H.-W. Lee, C. Cleveland, A. Szolnoki, When costly migration helps to improve cooperation, *Chaos: An Interdisciplinary Journal of Nonlinear Science* 32 (9) (2022) 093103.
- [42] X. Wang, M. Perc, Emergence of cooperation in spatial social dilemmas with expulsion, *Applied Mathematics and Computation* 402 (2021) 126149.
- [43] X. Wang, M. Duh, M. Perc, Robust cooperation against mutations via costly expulsion, *Europhysics Letters* 132 (3) (2020) 38001.
- [44] X. Wang, M. Duh, M. Perc, Pool expulsion and cooperation in the spatial public goods game, *Physics Letters A* 384 (18) (2020) 126391.
- [45] T. Ren, J. Zheng, Evolutionary dynamics in the spatial public goods game with tolerance-based expulsion and cooperation, *Chaos, Solitons & Fractals* 151 (2021) 111241.
- [46] Q. Pan, The influence of environment-based autonomous mobility on the evolution of cooperation, *Chaos, Solitons & Fractals* 172 (2023) 113320. doi:10.1016/j.chaos.2023.113320.
- [47] M.-J. Li, Y. Zhao, Long-range mobility and cooperation evolution under condition of different information amounts, *Chaos, Solitons & Fractals* 168 (2023) 113759. doi:10.1016/j.chaos.2023.113759.
- [48] X. Chen, F. Fu, Outlearning extortioners: unbending strategies can foster reciprocal fairness and cooperation, *PNAS Nexus* 2 (5) (2023). doi:10.1093/pnasnexus/pgad176.
- [49] S. Debove, N. Baumard, J.-B. André, On the evolutionary origins of equity, *PLOS ONE* 12 (3) (2017). doi:10.1371/journal.pone.0173636.
- [50] L. Boesch, R. Berger, Explaining fairness: Results from an experiment in guinea, *Human Nature* 30 (4) (2019) 453–470. doi:10.1007/S12110-019-09353-5.
- [51] J. Li, W. Wu, W.-X. Wang, B. Zhang, Data-driven evolutionary game models for the spread of fairness and cooperation in heterogeneous networks, *Frontiers in Psychiatry* 14 (2023). doi:10.3389/fpsyt.2023.1131769.
- [52] Y. Kim, J. C. Choe, G. Jeong, D. Kim, M. Tomonaga, Chimpanzees but not orangutans display aversive reactions toward their partner receiving a superior reward, *bioRxiv* (2018). doi:10.1101/274803.

- [53] A. Szolnoki, M. Perc, G. Szabó, Topology-independent impact of noise on cooperation in spatial public goods games, *Physical Review E* 80 (5) (2009) 056109.
- [54] A. Szolnoki, M. Perc, Reward and cooperation in the spatial public goods game, *Europhysics Letters* 92 (3) (2010) 38003.
- [55] X. Chen, A. Szolnoki, M. Perc, Competition and cooperation among different punishing strategies in the spatial public goods game, *Physical Review E* 92 (1) (2015) 012819.
- [56] A. Szolnoki, M. Perc, Competition of tolerant strategies in the spatial public goods game, *New Journal of Physics* 18 (8) (2016) 083021.
- [57] D. Helbing, A. Szolnoki, M. Perc, G. Szabó, Punish, but not too hard: how costly punishment spreads in the spatial public goods game, *New Journal of Physics* 12 (8) (2010) 083005.
- [58] A. Szolnoki, M. Perc, Group-size effects on the evolution of cooperation in the spatial public goods game, *Physical Review E* 84 (4) (2011) 047102.
- [59] P. Zhu, H. Guo, H. Zhang, Y. Han, Z. Wang, C. Chu, The role of punishment in the spatial public goods game, *Nonlinear Dynamics* 102 (2020) 2959–2968.
- [60] M. Wang, H. Kang, Y. Shen, X. Sun, Q. Chen, The role of alliance cooperation in spatial public goods game, *Chaos, Solitons & Fractals* 152 (2021) 111395.
- [61] C.-j. Zhu, S.-w. Sun, L. Wang, S. Ding, J. Wang, C.-y. Xia, Promotion of cooperation due to diversity of players in the spatial public goods game with increasing neighborhood size, *Physica A: Statistical Mechanics and its Applications* 406 (2014) 145–154.
- [62] M. H. Vainstein, J. J. Arenzon, Disordered environments in spatial games, *Physical Review E* 64 (5) (2001) 051905.
- [63] M. H. Vainstein, A. T. Silva, J. J. Arenzon, Does mobility decrease cooperation?, *Journal of theoretical biology* 244 (4) (2007) 722–728.