Rewarding policies in an asymmetric game for sustainable tourism

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ABSTRACT

Tourism is a growing sector worldwide, but many popular destinations are facing sustainability problems due to excessive tourist flows and inappropriate behavior. In these areas, there is an urgent need to apply mechanisms to stimulate sustainable practices. This paper studies the most efficient strategy to incentivize sustainable tourism by using an asymmetric evolutionary game. We analyze the application of rewarding policies to the asymmetric game where tourists and stakeholders interact in a spatial lattice, and where tourists can also migrate. The incentives of the rewarding policies have an economic budget which can be allocated to tourists, to stakeholders, or to both sub-populations. The results show that an adaptive rewarding strategy, where the incentive budget changes over time to one or the other sub-population, is more effective than simple rewarding strategies that are exclusively focused on one sub-population. However, when the population density in the game decreases, rewarding just tourists becomes the most effective strategy.

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1. Introduction

Among other objectives, the UN Agenda 2030 claims for sustainable modes of production and consumption, together with measures to protect and safeguard cultural and natural heritage [40]. One of the human activities requiring urgent actions in this direction is tourism. Nowadays, many cities, coastal resorts and natural areas are facing sustainable problems due to the massive affluence of visitors, which cause environmental degradation and affect the traditional cultural values in the destination [6,19,26,30]. As tourism is an activity involving human interaction, actors' behavior is a key factor for the industry to be sustainable [4,25]. Then, cooperation among those actors involved is necessary to achieve sustainable practices in the tourism sector.

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Cooperation conditions in games where defectors can free-ride the benefits obtained by the collaboration of others have been long analyzed in the scientific literature [3,27,32]. One of the mechanism to enforce the collaborative behavior is the application of incentives to the actors by means of punishment to defection or rewards to cooperation [28]. They have been mostly applied in the context of public good games [18,31,33,35], but also in other collective-risk dilemmas for climate change alleviation [14,34].

The objective of this this paper is to analyze the mechanisms to incentive sustainable practices in tourism. Specifically, we present here rewarding policies for the asymmetric tourism evolutionary model presented in [7]. In a nutshell, this model has two populations (or species) representing interactions between tourists and stakeholders or locals. Cooperation means to be sustainable while defection is understood as a tourist option that does not consider sustainability in the tourism transaction. There is a cost for the tourist when choosing sustainable tourism (the revenue for the stakeholder) and an additional cost to stakeholder for attending a tourist defector. Also, the game defines a tourist discomfort when the provided offer is not fulfilling their expectations.

We introduce in the model incentives to promote cooperation for both sub-populations of actors. Only few previous papers have included incentives in asymmetric games. For example, Gao et al. [13] propose a snowdrift game where two kind of species interacts, one adopting cooperation or defection strategy, and the other adopting cooperation or carrot-stick strategies, combining rewarding, or punishment according to the partner's strategy. Their results show that including these incentives enrich possible stationary outcomes whereas promoting cooperative behavior. Other authors have also analyzed the optimal incentives for promoting fairness in an ultimatum game, which is also an asymmetric game where players adopt two roles (i.e., proposer and receiver) [9,10]. Their results show that a selective rewarding according to the node centrality in a structured population reduces the promotion costs of fairness.

In this study we assume an external institution which provides incentives to participants, as it has been adopted by other studies for public good games [5] and collective risk dilemmas [8,14]. In our proposal, rewarding and punishment policies are equivalent. Thus, we focus on rewarding policies, which are mainly based on two parameters. The first one controls the per-capita incentive or budget and the second ones controls the budget share distributed to one or another sub-population. Three strategies are analyzed: (a) Rewarding tourists exclusively; (b) Rewarding stakeholders exclusively; (c) An adaptive rewarding, shifting from a full rewarding on one sub-population to the other depending on the level of cooperation at each time-step of the simulation of the evolutionary game.

The role of adaptive strategies has been analyzed before in the context of public good games and collective risk dilemmas [5,14,22,34,37,38]. Mostly, they find that mixture strategies combining of reward and punishing practices are the most convenient to enforce cooperation [5,14,22,37]. However, when cooperation must be achieved in smaller groups, the existence of institutional prevalence make that pure reward be the preferred strategy [34]. Moreover, when a *blind* hybrid strategy is adopted (i.e., it does not take into account the level of cooperation), pure punishment can be the optimal type of incentive [38]. Up to our knowledge, an adaptive strategy enforcing cooperation in one or another sub-population in asymmetric games as the one proposed here has not been analyzed yet in the literature.

Therefore, we apply here the rewarding policies on the evolutionary game on both unstructured (well-mixed) populations and on spatial lattice. In the second scenario, we define a density of the population that allows a migration process of the tourists through the lattice. In that way, the model emulates individuals' movements in a real tourism scenario. By running agent-based simulations [24] of the asymmetric evolutionary game we analyze the best static rewarding policies by modifying the parameter controlling the sub-population of individuals to target by the reward. This analysis is done under different conditions: well-mixed population, full density lattice without migration, and different densities with migration. Also, we compare the static and adaptive rewarding for different conditions of the spatial and unstructured population and parameters of the sustainable tourism game. Note that these diverse conditions emulate different tourism scenarios such as areas with low population density or *stressed* touristic areas with high population density (e.g., main touristic destinations and touristic coastal areas).

The rest of the paper is structured as follows. Next Section 2 includes all the methods used in the paper. Section 3 presents the results from the model and rewarding policies effects. Final insights and future lines are described in Section 4.

2. Methods

This section first includes the definition of the model from Sections 2.1 to 2.3. Later, in Section 2.4, the methodology for the analytical and agent-based simulations is described.

2.1. The asymmetric game and its payoffs

The evolutionary game is asymmetric since consists of a finite set of Z agents having two different and time invariant roles: being a tourist (T) or a stakeholder (S). The model satisfies that $Z = Z_T + Z_S$ with Z_T being the number of tourists and Z_S the number of stakeholders. All the players are distributed on the nodes of a social network. Specifically, we consider a regular lattice, given its simplicity with respect to other interaction networks such as scale-free networks but still ensuring the fundamental property of a limited players interaction range. Thanks to this limitation in the interaction range provided by the square lattice, we provide sufficient conditions to observe all possible results that are due to pattern formation in

Table 1
Payoffs matrix using a rewarding scheme where δ is the incentive and ω controls the asymmetric player to reward.

	Tourism Stakeholder (S)	
	C	D
Tourist (T)		
C	$1 - \epsilon + \omega\delta, \epsilon + (1-\omega)\delta$	$-1 - \tau + \omega\delta, 1$
D	$1 - \epsilon, \epsilon - \gamma + (1-\omega)\delta$	$-1, 1$

Table 2
Payoffs matrix using a punishment scheme.

	Tourism Stakeholder (S)	
	C	D
Tourist (T)		
C	$1 - \epsilon, \epsilon$	$-1 - \tau, 1 - (1-\omega)\delta$
D	$1 - \epsilon - \omega\delta, \epsilon - \gamma$	$-1 - \omega\delta, 1 - (1-\omega)\delta$

the studied system. The regular lattice has size $L \times L$, being $Z \leq L \times L$ so the lattice can have vacant cells. We call $\rho = \dfrac{Z}{L \times L}$ to the time invariant population density of the lattice and $\rho_T = 1 - \dfrac{Z_S}{Z}$ to the tourism pressure.

Independently from its role, an agent i from both populations can adopt two strategies: cooperation C or defection D. Tourist cooperators are noted by TC while tourist defectors are noted by TD. We use the same notations for stakeholders, being SC and SD the stakeholder cooperators and stakeholder defectors, respectively. The pair-wise interaction occurs between two players having opposing roles. A cooperating stakeholder SC offers a sustainable product or service to a tourist. A tourist can pay an additional cost $\epsilon \in [1, 2]$ for this sustainable transaction and obtains an added value, set to 1 for simplicity. On the other hand, the revenue obtained by the stakeholder from the sustainable transaction is equal to the additional cost ϵ paid by the tourist.

If a tourist player defects (TD) and is not sustainable when the stakeholder offers a sustainable asset, the cooperator stakeholder SC reduces her/his profit by an additional cost $\gamma \in [0, 1]$. Tourists, both cooperators TC and defectors TD, obtain the added value from the sustainable service ν minus its additional cost ϵ from the transaction with cooperating stakeholders. When a stakeholder adopts a defecting strategy SD, its payoff is a normalized value of 1 independently from the strategy followed by tourists. Cooperating tourists TC also pay a cost when stakeholders do not provide a sustainable asset, modeled by a discomfort parameter $\tau \in [0, 1]$. In this way, tourists obtain a lower payoff of $-1 - \tau$ if they adopt a sustainable or cooperation strategy C and they do not obtain the expected venue.

Finally, the model also considers a migration process for players having a tourist role. Tourist players move through the lattice at each time step t to a vacant neighboring cell independently from their strategy. In case there are more than one neighboring vacant positions, the agent picks one vacant position at random for the migration movement. Stakeholder players cannot move and keep the same position of the spatial cell during the simulation. If population density $\rho = 1$, the spatial lattice has no vacant positions and therefore, no migration is allowed.

2.2. Asymmetric rewarding for tourists and stakeholders

We introduce a rewarding approach for cooperating strategies for both players. ω controls the quantity of incentives δ goes for either tourists or stakeholders. When ω equals to 0, tourists are not rewarded and the whole incentive δ goes for stakeholders. The opposite is applied when ω equals to 1. Table 2.2 shows the payoff matrix for the asymmetric game having the rewarding mechanism

It is important to notice that, in the proposed model, rewarding and punishing schemes are equivalent. In fact, the alternative payoff matrix including punishment mechanism is obtained by subtracting $(1 - \omega)\delta$ and $\omega\delta$ to all the columns of the tourist and stakeholder's payoff in Table 1. The alternative payoff matrix which follows a punishment scheme is shown in Table 2.

2.3. Payoffs accumulation and players' strategy update

Players of both roles interact with their direct neighbors in a pairwise interaction in the lattice. A focal player i only plays with those having opposing roles and accumulates its payoff in Π_i from all its interactions if at least there is one possible interaction; being four the maximum number of possible interactions if all the neighboring cells are occupied by agents of opposing roles.

The dynamics of the game includes an imitation process of the neighboring agents in the spatial lattice and a mutation to randomly change the strategies of the players at every time step t. A player i changes its strategy at random with a

mutation probability μ and imitates the strategy of a local neighbor with probability $1 - \mu$. As players will keep their role for the whole simulation, they can only imitate other players in the lattice having the same role in the game. After playing the pairwise interactions in the lattice and accumulating its payoffs in Π_i, a player i has the opportunity of updating its strategy according to this payoff value in previous time step $t - 1$ and the ones from their neighbors.

In this imitation process, a player i imitates a player j having the same role as i with a probability $p_{i \to j}$ that increases with their payoff difference ($\Pi_j - \Pi_i$, being Π_i and Π_j the payoffs of i and j in $t - 1$, respectively), as done in [39]:

$$p_{i \to j} = \frac{1}{1 + e^{-(\Pi_j - \Pi_i)/\kappa}}, \tag{1}$$

where the amplitude of noise κ equals to 0.1 as done in [43,44]. It is important to notice that a player j cannot be imitated if it did not interact with any other player and did not accumulate any payoff in previous time step $t - 1$. This can happen if, for instance, a player is isolated in the lattice or all the neighboring players have the same role.

2.4. Methods' details for simulating the model

The update rule in this game defines a Markov process representing the evolution of the number of cooperators at every time step. In the case of a finite and unstructured population, the asymptotic steady state of the number of cooperators can be studied by applying convergence results of ergodic Markov chains. As the process includes probabilistic mutation (μ), the population does not fixate in any stationary state. Thus, instead of computing the probability of fixation in each absorbing state, we can make use of the stationary distribution of this Markov chain to analyze the asymptotic state of the population, and assess the pervasiveness in time of a each fraction of cooperators.

We use Monte-Carlo (MC) agent-based simulations [2,24] for simulating the asymmetric model on spatial regular lattice. Source code of the agent-based simulation engine, programmed in Java, is available to be downloaded at www.manuchise. com/sustainable-tourism. The evolution of the population proceeds in discrete steps involving the payoffs accumulation, update rules, and migration processes in line with the dynamics described above. The mutation (or exploration) probability (μ) equals $\frac{1}{Z}$ in all experiments. For the agent-based simulations, the size of the population is $Z = 4.9 \times 10^3$ in a squared regular lattice of 70×70 with periodic boundary conditions and Von Neuman neighborhood. Each node of the lattice is either vacant or occupied by one player. The vacant positions are given by density ρ. We run the model for 30 independent MC realizations and a maximum number of 10^3 synchronous time steps, where all the realizations reach a stationary stable state and deviation from the MC realizations is low. Finally, all the simulation results were obtained by averaging the last 25% of the simulation time steps in the independent MC realizations.

3. Simulation results

In this section, we analyze the most effective and efficient rewarding for participants (tourism and stakeholders) to adopt sustainable behavior when interacting. In other words, we analyze the specific allocation of rewarding that maximizes the final cooperation in the population. First, we analytically study these conditions in the simple case of a finite and unstructured population in Section 3.1. Later, we evaluate how population density and migration in the spatial game affect the outcome of the model through computational simulations (Section 3.2).

3.1. Rewarding in a finite and unstructured population

In this subsection, we will find the general conditions on the reward parameters (ω and δ) that maximizes the probability of cooperation in the asymptotic stable equilibrium of the game. Instead of the regular lattice, here we assume that the two sub-populations (tourist and stakeholders) are located in well-mixed graph, where only individuals belonging to different sub-populations can interact.

Appendix A includes the details of the calculation of optimum reward distribution, based on the theoretical results on fixation probabilities for bimatrix games in finite populations [29]. These results assume null mutation ($\mu = 0$) and weak imitation process ($\kappa >> 0$). Given these conditions, the optimum ω^* follows this rule:

$$\omega^*(k_T, k_S) = \begin{cases} 0 & if \quad k_S/Z_S < r_{T,S} k_T/Z_T + 1 - r_{T,S} \\ 1 & if \quad k_S/Z_S > r_{T,S} k_T/Z_T + 1 - r_{T,S} \end{cases}$$

Therefore, an adaptive incentive policy optimizes the probability to achieve full cooperation. This policy depends on the relative status of cooperation between the two populations at every time step. To make the interpretation of the switching point easier, let us analyze the case of identical population $Z_T = Z_S$. Under this assumption, it would be optimal to reward exclusively tourist $w^* = 1$ when the number of tourist cooperators is lower than the number of stakeholder cooperators $k_T < k_S$. The opposite (reward exclusively stakeholders, $w^* = 0$) occurs when the number of tourist cooperators is larger than the number of stakeholder cooperators $k_T > k_S$.

In order to test this incentive policy in a more general setting ($\mu > 0$ and $\kappa > 0$), we will find the stationary distribution of the Markov chain defined by the evolutionary game model. First, we calculate the transition probabilities of this Markov
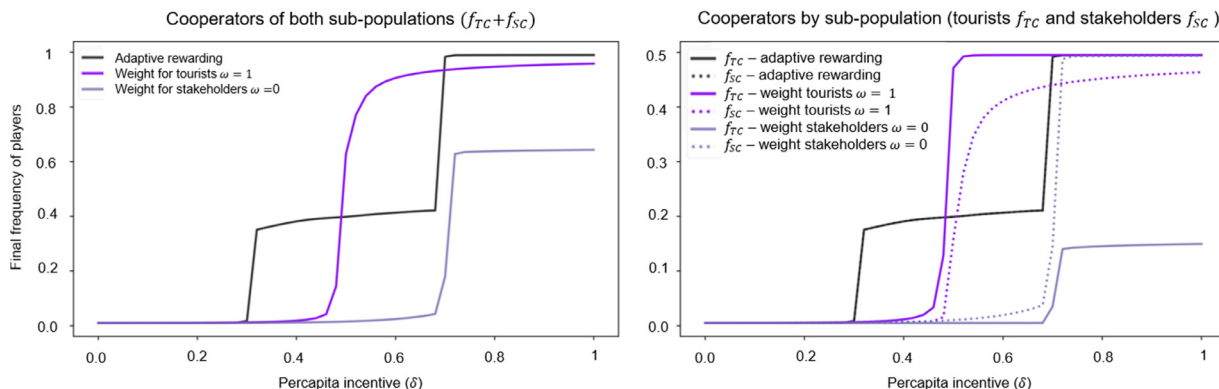
Fig. 1. Final frequency of players (f_{TC} stands for tourist cooperators and f_{SC} for stakeholder cooperators) under three different policies of tourists reward (ω) and assuming well-mixed, finite population, and strong selection ($\kappa = 0.2$). Incentives for tourists are more efficient. Adaptive rewarding is the best option for low and high percapita values δ. The rest of parameters are $\epsilon = 1.0$, $\gamma = 0.5$, $\tau = 0.5$, $Z_T = Z_S = 50$, $\mu = 0.01$.

process. In a well-mixed population, all tourist and stakeholders are equally likely to interact. Then, given a certain cooperation state in the two populations $\mathbf{x} = (x_T, x_S)$, with $x_T = k_T/Z_T$ and $x_S = k_S/Z_S$, the probability to increase by one the number of cooperators in population $h \in \{T, S\}$ is

$$T_h^+(\mathbf{x}) = (1 - x_h)\left((1 - \mu)x_h \frac{1}{1 + e^{-(f_h^C(\mathbf{x}) - f_h^D(\mathbf{x}))/\kappa}} + \mu\right)$$

and the probability to decrease by one the number of cooperators in population h is

$$T_h^-(\mathbf{x}) = x_h\left((1 - \mu)(1 - x_h)\frac{1}{1 + e^{-(f_h^D(\mathbf{x}) - f_h^C(\mathbf{x}))/\kappa}} + \mu\right),$$

where $f_h^C(\mathbf{x})$ and $f_h^D(\mathbf{x})$ are the expected payoff or fitness of the cooperator and defector, respectively. Given the payoff matrix in Table 2.2, the expressions for these expected payoffs are:

$$\begin{aligned}
f_T^C(\mathbf{x}) &= (-\tau + \omega\delta)(1 - x_S), \\
f_T^D(\mathbf{x}) &= -\omega\delta x_S, \\
f_S^C(\mathbf{x}) &= (\epsilon - \gamma - 1 + (1 - \omega)\delta)(1 - x_T), \\
f_S^D(\mathbf{x}) &= (1 - \epsilon - (1 - \omega)\delta)x_T.
\end{aligned}$$

The transition probabilities define a Markov process in two dimensions. The stationary distribution $\bar{p}(x)$ of this Markov chain provides the expected asymptotic steady state of the evolutionary game. This is calculated by following the same procedure in [41]. We firstly calculate the univariate transition matrix $W_{y,y'}$ defined from a bi-ojective function $y = V(x_T, x_S)$, $y \in \mathbb{N}$, and secondly the stationary distribution of $\bar{p}(x)$ is obtained by computing the normalized eigenvector corresponding to eigenvalue 1 of the transpose of matrix $W_{y,y'}$. The marginal distributions of $\bar{p}(x)$ provide the stationary distributions of tourist and stakeholder population, respectively.

Figure 1 further analyzes the question of the optimal assignment of the incentive to cooperate by representing the relationship between budget δ and stationary cooperation for different allocations w. In all cases, full defection is expected when budget is null ($\delta = 0$). Cooperation levels start to increase when increasing the budget. However, it is clearly more efficient to allocate the incentive to the tourist population ($\omega = 1$) than to the stakeholder population ($\omega = 0$), since we obtain higher global population levels starting from lower budget assignment. Moreover, excepting from a budget located in a medium range, the adaptive assignment obtains higher cooperation levels than any extreme allocation.

To complete the analysis for the case of well-mixed population, Figure 2 presents the stationary distribution for all possibilities of the allocation $0 \leq \omega \leq 1$ and a wide range of values of the revenue of the stakeholder ϵ and tourist discomfort when receiving an unsustainable product or service τ, respectively. The budget is fixed at $\delta = 0.75$. The panels show that the effect of the revenue of stakeholders in cooperation is practically non-existent, excepting for the stakeholder cooperation in extreme low values of this revenue and almost null allocation of the incentive in this population. However, the steady state of cooperation in the two populations is more influenced by high values of the tourist discomfort τ, although slightly dampened by increasing the reward allocation in the tourist population.
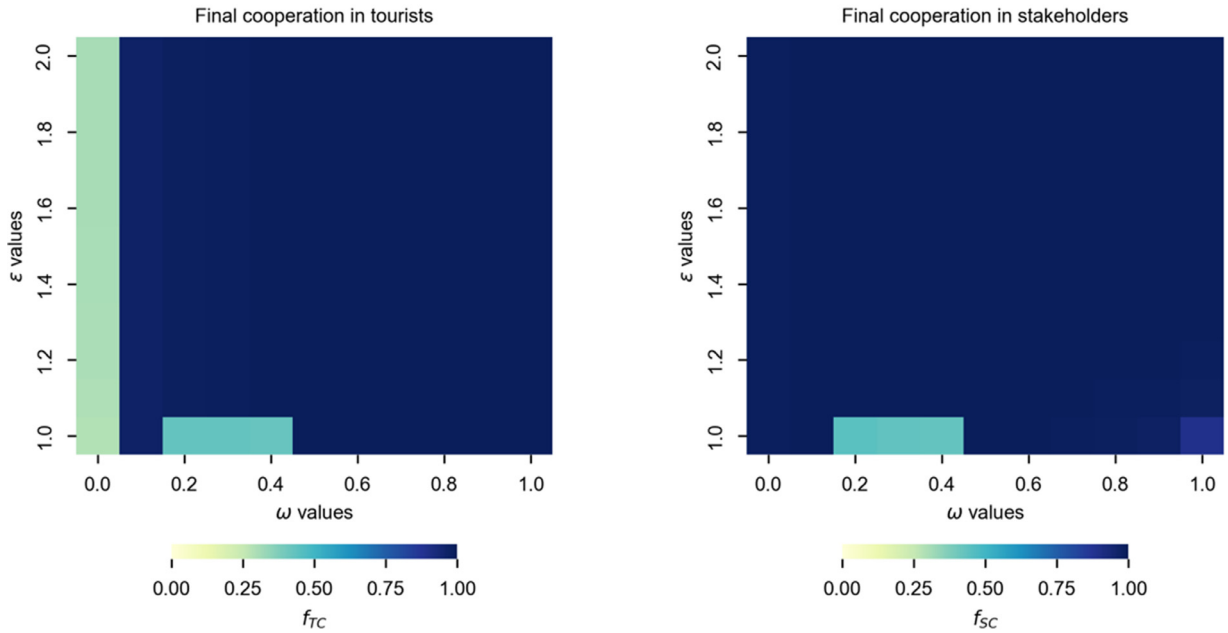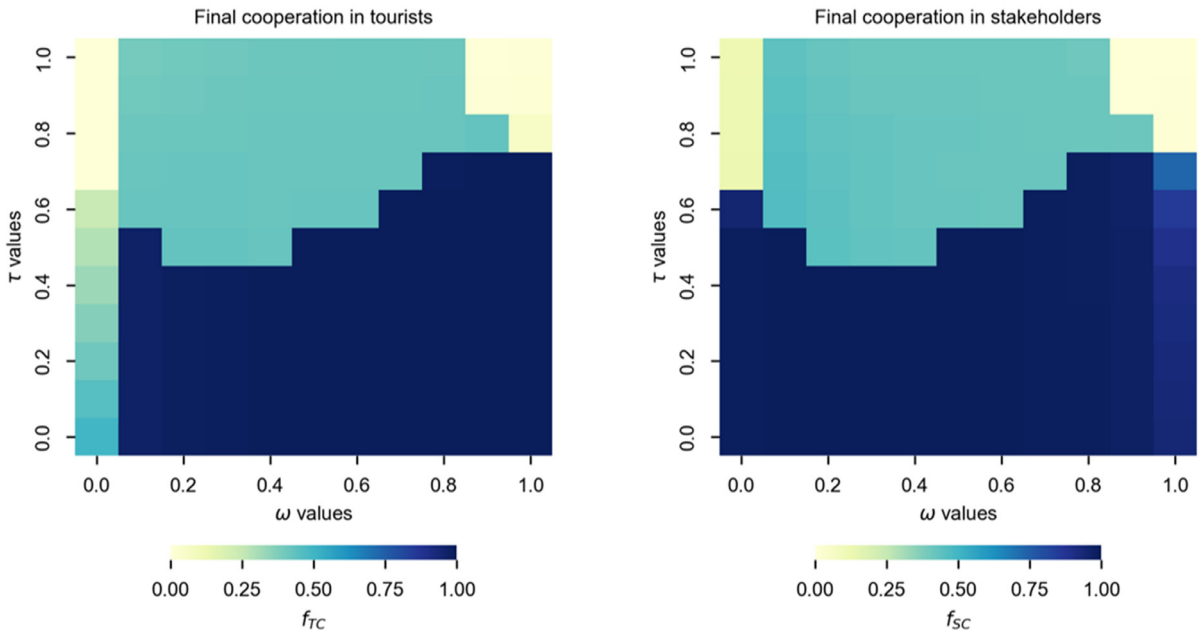
Fig. 2. Heatmaps showing two sensitivity analysis. Two heatmaps of the first row of the panel for ϵ (tourist cost in the game) and ω (rewarding policy). Two heatmaps of the last row of the panel for τ (tourist discomfort in the game) and ω (rewarding policy). Plots show final frequency of tourist cooperators f_{TC} (figures on the left) and stakeholders cooperators f_{SC} (figures on the right) for well-mixed and finite population. Incentives on stakeholders are not relevant to increase sustainable tourism. The rest of parameters are $\gamma = 0.5$, $\tau = 0.5$, $\delta = 0.75$, $Z_T = Z_S = 50$, $\mu = 0.01$.

3.2. Rewarding results in a spatial game with migration

We extend here the analysis of the effect of rewarding strategies when the asymmetric game is played in a structured network (lattice) including migration. Fig. 3 shows the cooperation levels achieved in the regular lattice assuming three different scenarios of the population density ($\rho \in \{0.5, 0.8, 1\}$). In the latter case ($\rho = 1$), migration is not allowed.
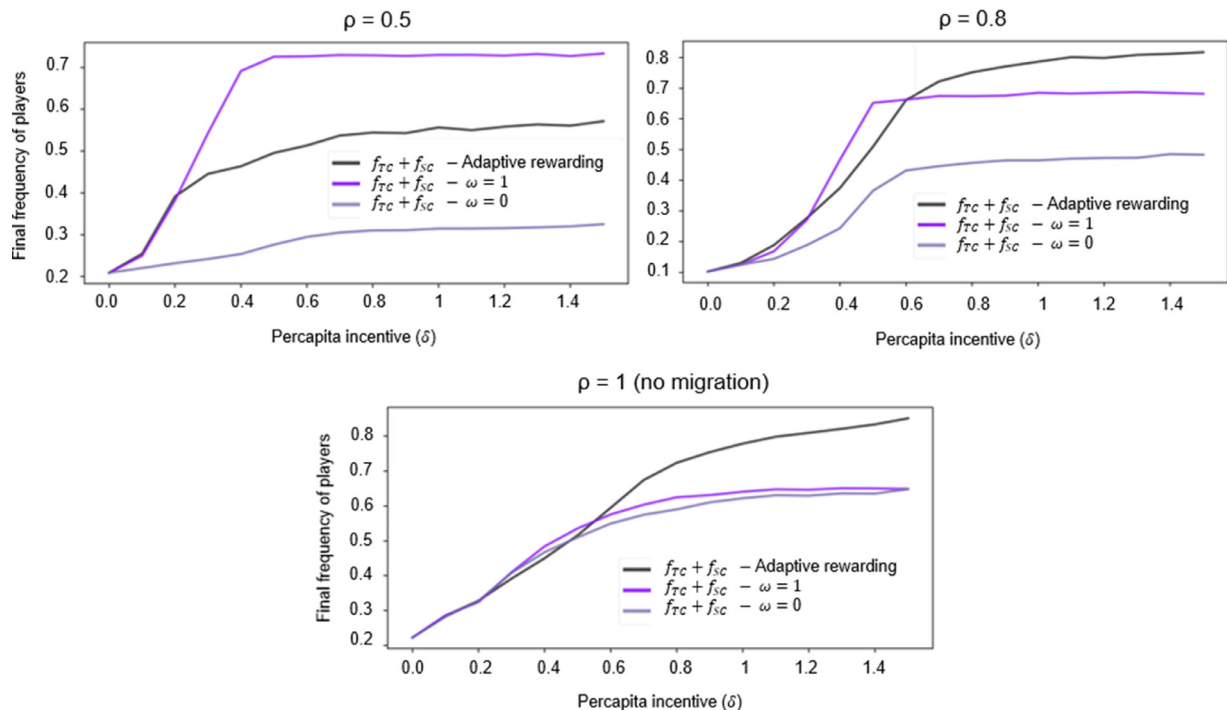
Fig. 3. Final frequency of players (f_{TC} stands for tourist cooperators and f_{SC} for stakeholder cooperators) when running sensitivity analysis on δ for different densities in the lattice ($\rho = \{0.5, 0.8\}$ with migration and $\rho = 1$ with no migration). We evaluate three rewarding strategies: a) rewarding tourists ($\omega = 1$), b) rewarding stakeholders ($\omega = 0$), and c) adaptive rewarding. Plots show that adaptive rewarding is the best strategy in dense populations while, under sparse conditions and migration, rewarding tourists is the best option.

When assuming high enough population density and migration, the adaptive rewarding strategy obtains the highest global cooperation levels of the three strategies selected excepting a certain range of medium values of incentive budget δ. In addition, the cooperation levels of the two populations (stakeholders and tourists) are identical and both add more global cooperation than in the other cases of two extreme allocation of the incentive. These results match with the case of well-mixed population, although cooperation is not full in the spatial game.

Noteworthy, when the population density is low enough ($\rho = 0.5$), the adaptive rewarding is not the optimal one, but allocating the incentive to the tourist population ($\omega = 1$) is the best to promote cooperation in the sustainable tourism game. In this scenario of sparse population, although migration allows new interactions between tourists and stakeholders, these interactions are rather low and make more efficient allocate the budget to incentive tourists.

Fig. 5 and 4 show two panels with heat-maps for a sensitivity analysis on ϵ and τ for adaptive rewarding and non-adaptive rewarding, respectively. The rewarding policies are applied under three density values (0.5, 0.8 and 1). Again, when density is decreasing, even if migration occurs, cooperation in tourists decreases as well when considering adaptive rewarding. In that case, rewarding tourists is more beneficial. When we set a full density lattice ($\rho = 1$) or even high density $\rho = 0.8$ with migration, the adaptive rewarding is the best option in general. Rewarding stakeholders ($\omega = 0$) is not a good choice.

Finally, Figure 6 shows the final cooperation levels in the two sub-populations for three density values (0.5, 0.8, 1). In this experiments, we set variations in reward allocation ω and revenue for stakeholders ϵ so the rewarding strategy is not adaptive. By comparing these results with the ones obtained in the analytical study of Fig. 2, it is clear that the spatial effect makes that cooperation further decreases in one population when the allocation of the reward focuses on the other population. When tourist population density is high enough and migration is allowed, the agents in the two populations have more chances to interact. Then, the results of cooperation in the long term resemble those obtained with well-mixed cooperation.

4. Final discussion

The proposed asymmetric model represents how tourists and stakeholders interact in a sustainable or unsustainable manner. Then, the objective of this paper is to study the best way to reward sustainable activities to increase the cooperation. Previous contributions on strategies to enhance cooperation are based on combining rewarding and punishing policies
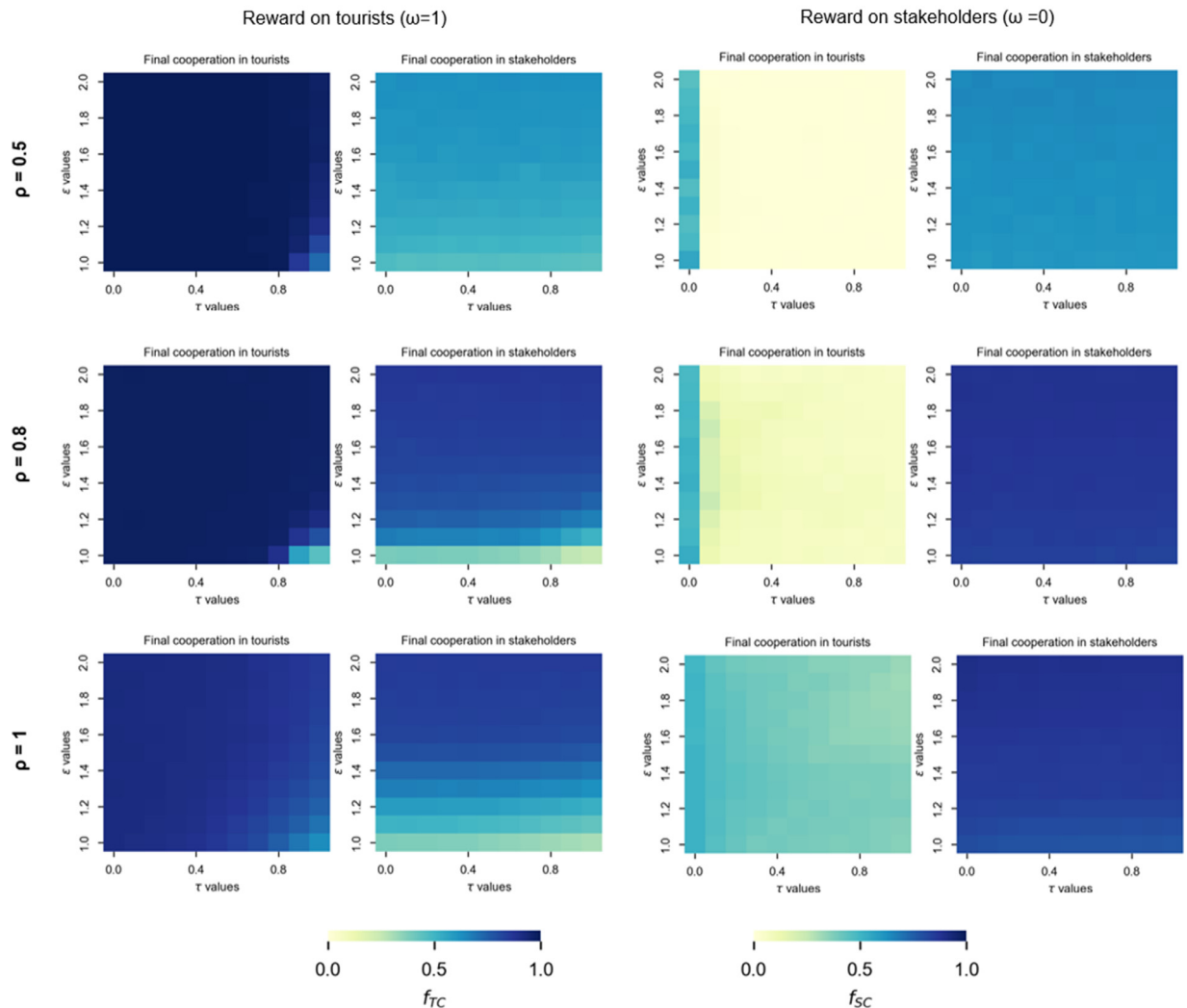
Fig. 4. Sensitivity analysis on ϵ (tourists cost of the game) and τ (tourists discomfort) for non-adaptive rewarding, either focus on tourists ($\omega = 1$) or cooperators ($\omega = 0$), showing final frequency of tourist cooperators f_{TC} and stakeholder cooperators f_{SC}.

for a single population of individuals in traditional symmetric games [5,14–16,18,34,38]. Previous contributions obtained different results regarding the preference for rewarding and punishing strategies. In the pairwise asymmetric game presented in this paper, punishment and rewarding strategies are equivalent, so the study focuses on the optimal allocation of the budget to incentive cooperation in one or another sub-population of individuals (i.e., tourists and stakeholders in our game). Then, the analysis provides new aspects to the problem of incentives in evolutionary games model.

In the proposed asymmetric game with unstructured population, the adaptive strategy of allocating incentives depending on the current cooperation presents higher cooperation levels than extreme strategies of allocating incentives exclusively to one or another population. The preference for hybrid strategies for enforcing cooperation agrees with other studies focusing on carrot and stick strategies for public good games [5,36] and also in collective risk dilemmas for controlling climate change [14]. An adaptive rewarding policy that depends on the centrality measure of the nodes was recently shown as one of the most efficient strategies for the asymmetric ultimatum game [9].

When playing in a spatial lattice with migration, the preference for adaptive strategies remains excepting for the case of low population densities, where the extreme strategy of rewarding the sub-population of sustainable tourists is more effective. Rewarding stakeholders is not an optimal choice in all the tested scenarios. Previous findings in the context of spatial public good games show that low population densities can revert the benefits of social mobility to enhance cooperation [20]. Our study reveals the disruptive effect of low densities also when determining the optimal strategy to enforce cooperation.

Besides achieving higher level of cooperation, the adaptive strategy includes other benefits for sustainability beyond the higher volume of cooperation. For example, when implementing this strategy, the cooperation levels in the two popula-
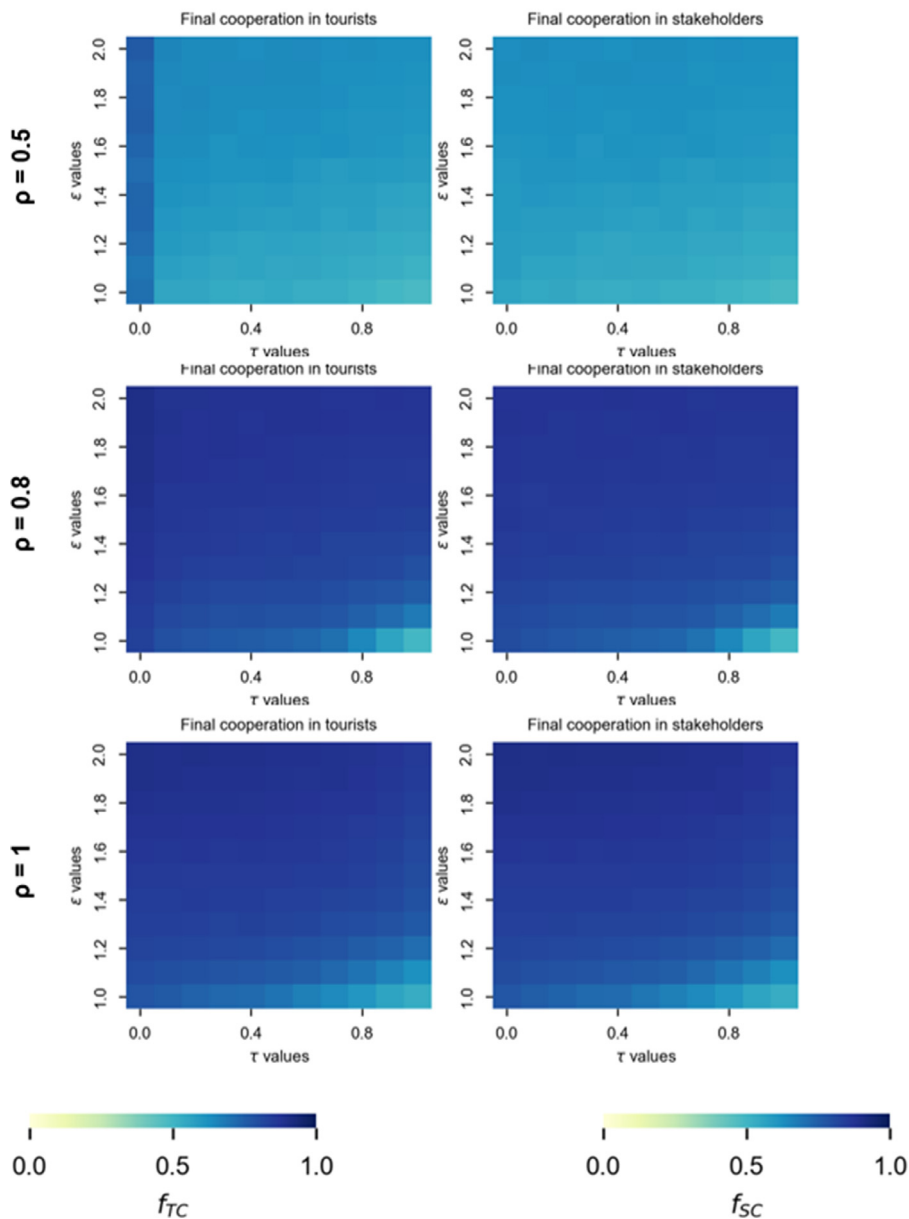
Fig. 5. Sensitivity analysis on ϵ (tourists cost of the game) and τ (tourists discomfort) for adaptive rewarding, showing final frequency of tourist cooperators f_{TC} and stakeholder cooperators f_{SC}.

tions are similar. This equilibrium between the two populations (stakeholders and tourists) favors a more stable sustainable situation than other outcomes where one population cooperates significantly more than the other. Moreover, the adaptive strategy also favors cooperation levels in situations of low added value of sustainable practices by stakeholders.

This study presents limitations. For instance, the studied networks are homogeneous in terms of connections. Also, the migration mechanism is basic (i.e., random movement of a tourist to an empty neighboring cell of the lattice). This migration does not fully model the realistic case of tourists' interactions with stakeholders or locals. Then, we can further study more realistic ways of migration in games by including mechanisms such as aging effects [1], multidimensional mobility [23], or conditioned to factors dependent on the individual's environment [12]. Researchers can also analyze the case of a volunteer contribution for rewarding cooperators coming from the population itself. This mechanism has been implemented in previous studies [15,18,21,34,35,38], instead of considering an external institution that enforces cooperation.
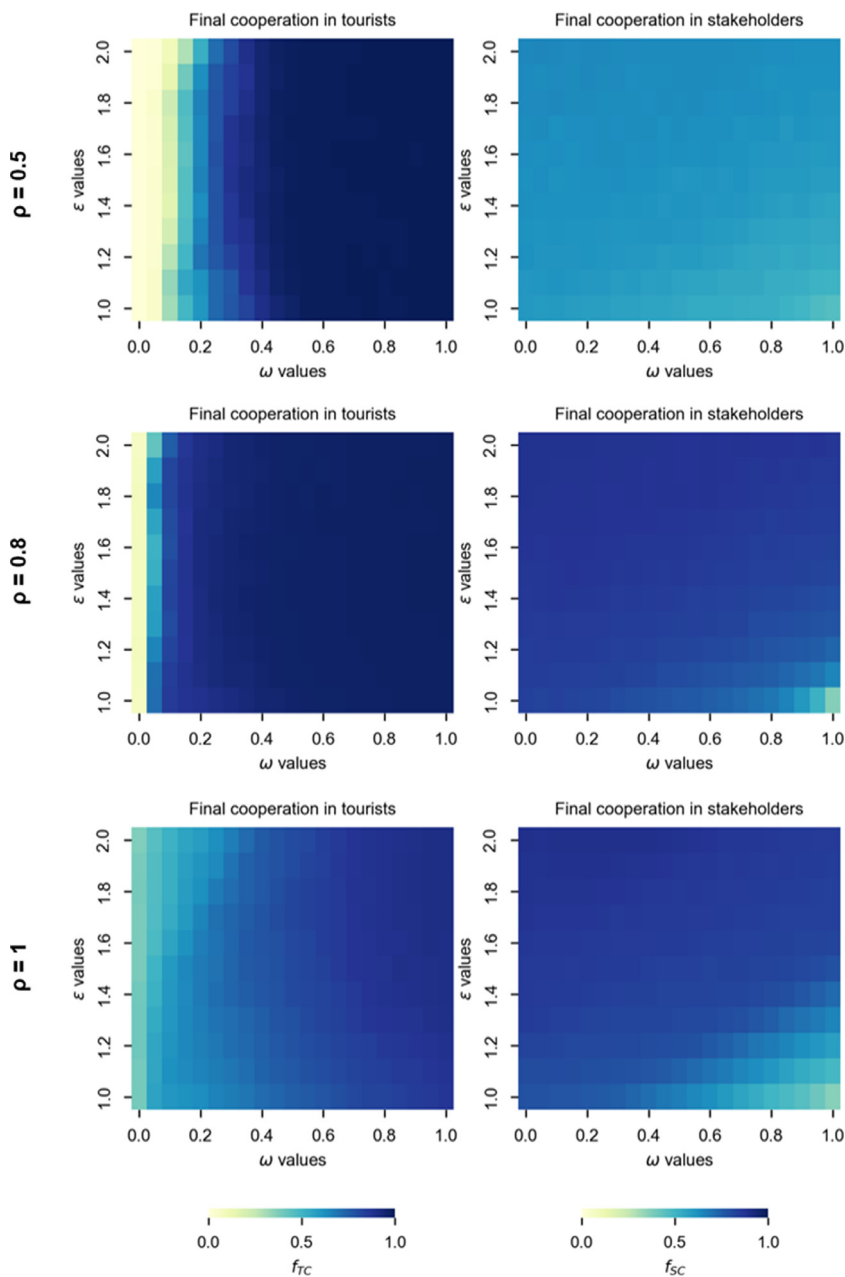
Fig. 6. Final cooperation (f_{TC} stands for tourist cooperators and f_{SC} for stakeholder cooperators) when running a sensitivity analysis on ϵ (tourists cost in the game) and ω (weight for rewarding) under different values of population density ρ. As ω is changing, we show the implications of using a pure rewarding for the two sub-populations. When ρ is lower than 1, tourists can migrate through the empty positions of the lattice. The rest of parameters are $\gamma = 0.5$, $\tau = 0.5$, $\delta = 0.75$, lattice with $Z = 4,900$, $\mu = 0.01$.

Finally, we select in our study the best strategy in terms of the maximum level of final cooperation, disregarding the total costs of interference, as it has been done in previous papers for prisoner's dilemma and public goods games [11,17,42]. These studies propose selective rewarding strategies according to the percentage or cooperators and node centrality which obtains higher cooperation levels and lower costs than fixed strategies. Future works can follow this line by extending the incentive mechanisms for asymmetric tourist-stakeholder and other asymmetric games by including this kind of adaptive strategies.

Appendix A. Calculation of the optimum reward allocation

We calculate in this appendix the strategy of reward allocation that maximizes the long-term number of cooperators. It is based on the results on fixation probabilities for bimatrix games in finite populations [29].

In this context, we define $\rho_{(k_T, k_S) \to (Z_T, Z_S)}$ as the fixation probability that given an initial number of cooperators in the tourist population of k_T and k_S, respectively, the long-term steady state gives full cooperation in both populations. A closed expression for this fixation probability in terms of model parameters can be found in [29]. That paper assumes a frequency-dependent Moran process for strategy update, the player's fitness dependent on the average pay-off and weak selection. The extension of the results in [29] to the case of pairwise interaction is straightforward. Thus, given null mutation ($\mu = 0$) and weak imitation process ($\kappa >> 0$), the fixation probability follows the expression:

$$\rho_{(k_T, k_S) \to (Z_T, Z_S)} = \frac{k_T}{Z_T} \frac{k_S}{Z_S} \begin{pmatrix} 1 + \frac{1}{\kappa}(Z_T - k_T)(Z_T + k_S)(a_{11} - a_{12} - a_{21} + a_{22}) \\ +(Z_T - k_T)(Z_T + Z_S)(a_{12} - a_{22}) \\ +(Z_S - k_S)(Z_S + k_T)(b_{11} - b_{12} - b_{21} + b_{22}) \\ +(Z_S - k_S)(Z_S + Z_T)(b_{21} - b_{22}) \end{pmatrix}.$$

Substituting the expression of the elements in the payoff matrix and after some simplification, we finally obtain,

$$\rho_{(k_T, k_S) \to (Z_T, Z_S)} = \frac{k_T}{Z_T} \frac{k_S}{Z_S} \begin{pmatrix} 1 + \frac{Z_T Z_S}{\kappa} \delta \left(1 - \frac{k_S}{Z_S}\right)\left(\frac{1}{r_{T,S}} + 1\right) \\ +(\epsilon - 1)\left(1 - \frac{k_S}{Z_S}\right)\left(\frac{1}{r_{T,S}} + 1\right) \\ -(\tau + \gamma)\left(1 - \frac{k_T}{Z_T}\right)\left(1 - \frac{k_S}{Z_S}\right) \\ -\delta\omega\left(\left(\frac{k_S}{Z_S} - \frac{k_T}{Z_T}\right) - \left(1 - \frac{k_T}{Z_T}\right)r_{T,S} + \left(1 - \frac{k_S}{Z_S}\right)\frac{1}{r_{T,S}}\right) \end{pmatrix},$$

where $r_{T,S} = \frac{Z_T}{Z_S}$ is the ratio between tourist and stakeholder population. As it can be observed, the fixation probability is linear with respect to which population benefits more from the incentive, ω. The fixation probability is maximized in one of the two extreme values of the interval $0 \le \omega \le 1$. The specific maximum depends on the sign of the term in brackets at the right hand side of ω. If this term is positive, the maximum fixation probability is obtained in $\omega^* = 0$, and if it is negative, the maximum fixation probability is achieved in $\omega^* = 1$. The term is zero when $\bar{k}_S/Z_S = r_{T,S}\bar{k}_T/Z_T + 1 - r_{T,S}$. In this case, any incentive policy is optimal. Then, the optimum ω^* follows this rule:

$$\omega^*(k_T, k_S) = \begin{cases} 0 & if \quad k_S/Z_S < r_{T,S}k_T/Z_T + 1 - r_{T,S} \\ 1 & if \quad k_S/Z_S > r_{T,S}k_T/Z_T + 1 - r_{T,S} \end{cases}$$

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