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SUCCESS BIASED IMITATION INCREASES THE PROBABILITY OF EFFECTIVELY DEALING WITH ECOLOGICAL DISTURBANCES

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ABSTRACT

Ecological disturbances (i.e. pests, invasive species, floods, fires etc.) are a fundamental challenge in managing connected social-ecological systems. Even if treatment for such disturbances is available, often managers do not act quickly enough or not at all. In this paper we build an agent based model that examines: a) under what circumstances are managers locked into non-action that favors ecological disturbances? b) what learning strategies are most effective in avoiding management lock-in? The model we develop relates adoption of treatment strategies to eradicate ecological disturbances with the type of learning preferred by individuals (success bias, conformist and individual). We further model treatment strategy adoption as a function of treatment cost, ability of the ecological system to recover once treated and the disturbance effect on the social system. Our model shows the importance of success-bias imitation and system size in affecting the odds of eradicating ecological disturbances on connected landscapes.

1 INTRODUCTION

Agriculture, biodiversity and human well-being are interrelated and depend heavily on the effective management of pests, invasive species, fires, floods and, more generally, of ecological disturbances (Pimentel et al. 2000, Chapin III et al. 2000). Ecological disturbances are important topics in international policy (Howden et al. 2007). Further, while some ecological disturbances can be prevented but have a clear and immediate effect (i.e. fires and floods), others such as invasive species and pests can be very hard to detect and their effects can be slow, but cumulative and potentially devastating (Chadès et al. 2008, Chadès et al. 2011, MacKenzie et al. 2002). In an increasingly interconnected world it is important to understand how individuals manage ecological disturbances effectively, how they make decisions about adopting treatment strategies and how these can spread through an interconnected social-ecological system. Environmental management often requires cooperation or coordination on the part of managers, and therefore the transmission of information among managers about management strategies and environmental conditions (Epanchin-Niell et al. 2009, Lansing and Kremer 1993, Janssen 2007). This is especially true in fragmented landscapes composed of different types of land-tenure regimes with managers distributed across a patchy, connected ecological landscape (Epanchin-Niell et al. 2009, Rebaudo and Dangles 2011, Schoon et al. 2014).

Management practices need to be adopted at appropriate scales, as a mismatch between management and the associated ecological system can lead to inefficient management or complete failure (Crowder et al. 2006, Cumming et al. 2006, Folke et al. 2007). Given the connectivity of the overall social-ecological system, reliance on trial and error learning may be detrimental. To complicate matters further, increased connectivity is accompanied by an increased uncertainty associated with the magnitude of ecological

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disturbances and the uncertainty related to strategies adopted by neighbors (Darnhofer et al. 2010, Rebaudo and Dangles 2015, Baggio and Janssen , Baggio et al. 2015). Individuals need to adapt management strategies to changing conditions in the face of uncertainty, and thus will rely not only on individual learning but also on social learning (Baird et al. 2016). Managers seek out and use information from their peers (Isaac et al. 2007, Baird et al. 2016). Personal networks are a fundamental component of the decision making process. Trusted individuals (often successful individuals, or just the majority of peers) play a key role in diffusing and adopting specific management practices (Collins 2014).

Individuals will adopt different strategies when the ones they use are unproductive, when specific strategies are adopted by the majority of their peers (or other individuals in their social network), or are adopted by the most successful individuals within their social network (Laland 2004, Mesoudi 2011). More precisely, individuals employ social learning if the returns of the strategy adopted by neighbors is considered a better option than the strategy they are currently using (Schlag 1998). There are two key ways in which individuals learn socially: 1) success-biased imitation, where individuals copy strategies adopted by successful individuals (Boyd and Richerson 1988), and 2) conformist imitation, in which individuals adopt the most common strategy within the population, independent of the actual payoff (Henrich and Boyd 1998).

This study aims to provide some theoretical insight into the relationship between social and individual learning and the effect of ecological disturbances using an agent-based modeling (ABM) framework. We use a social-ecological model to assess the conditions that lead to successful management of ecological disturbances such as pests and invasive species under full isolation or full connectivity between social agents in a fully connected ecological landscape. We do this by varying the cost of treatment, the effect of the ecological disturbance on the ecological system (catastrophic vs non catastrophic) and the type of learning agents employ. We examine the differential effect of learning via trial and error, or learning socially either by imitating other successful managers, or by imitating the majority of other managers in the social-ecological system. We assume that the ecological landscape is fully connected and thus disturbances have the ability to affect the whole system simultaneously. We find that, on average, success-biased imitation is key to the management of ecological invasions.

2 METHODS

The model can be thought of a generalization of the well known Lansing-Kremer (Lansing and Kremer 1993, Janssen 2007) and comprises N social agents and N ecological patches. Each ecological patch is associated with a social agent. Ecological patches can be affected by ecological disturbances, and social agents can intervene to prevent or treat such disturbances. Affected ecological patches suffer a reduction in utility (yield, aesthetic value, etc.) that reduces the payoff of social agents. Payoffs are a function of the difference between utility gained from the ecological patch and the cost of management practice employed (cost = *csl* if treatment is adopted, and 0 otherwise). Treatment adoption treats the ecological disturbance (or the possibility of being ”disturbed”). Treatment adoption needs to be maintained or its effects vanish. Treatment is adopted as a function of learning strategy (individual, success bias, or conformist bias). Agents decide the type of learning strategy depending on their preference towards individual vs social learning, whether they are success-biased or conformist imitators and their observed payoffs. Social agents are either isolated (thus engaging only in individual learning), or they exist in homogeneously mixed environments, where a social agent has the ability to know strategy and payoff of all other social agents in the system. Model details and model code can be found at https://www.openabm.org/model/5005/version/1/view. The flowchart below gives a graphical representation of the process just described (Figure1).

2.1 Model Initialization and Parameter values

At the beginning of each simulation run, 10% of ecological patches are affected by a generic disturbance. Social agents are not adopting any treatment by default. The model initial parameters are reported in Table 1.

Table 1: Symbols, names and values of model parameters.

Type	**Symbol**	**Variable**	**Value**
General	Ns	Number of social agents	10 or 100
	Ne	Number of ecological patches	= Ns
	csl	Cost of adopting the disease management strategy	10, 50
	rec	Recovery of yield when cured (pest is eliminated)	0 (no recovery), 10
	eff	Loss of utility due to infection	10, 50, 100
Social Agents	$Net?$	Type of social network	Isolated, fully connected
	mem	Memory (payoff remembered)	5
	$confid$	Social learning confidence	3
	$lprob$	conformist probability (success learner = $1-lprob$)	0, 0.25, 0.5, 0.75, 1
	A	Adoption of treatment	0
	mu	Mutation (or learning error)	0.02
	th	Parameter for conformist bias imitation	3
Ecological Patches	y	Utility provided	100
	$Eres$	Patch intrinsic resistance to disturbance	0, 0.25, 0.4, 0.5, 0.6, 0.75
	$Ninf$	Fraction of initially infected ecological patches	10%

2.2 Ecological Disturbances

Ecological disturbances are represented by pests, invasive species, fungi, fires, floods etc. on fully connected landscapes. Here $Ninf$ represents the fraction of initially affected patches in the ecological system. At each time-step ecological patches have a probability of being affected by a disturbance that is dependent on the number of ecological patches already affected within the overall system. Ecological patches become affected if $Iag > Eres$ where Iag is disturbance strength represented by a number extracted from a uniform

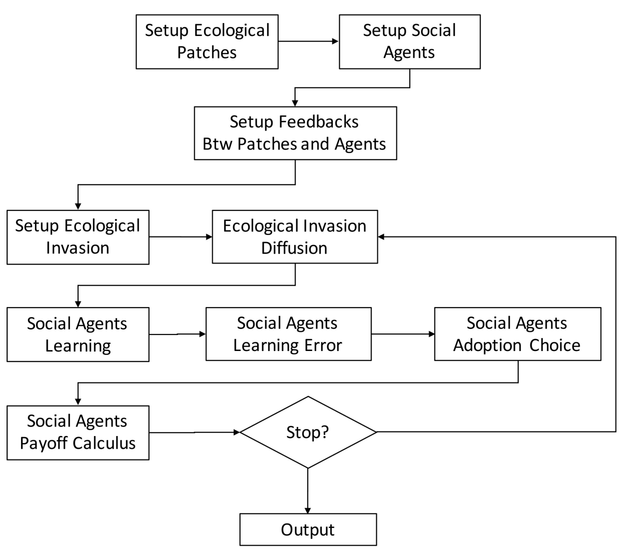

Figure 1: Model Flowchart Diagram

random distribution between 0 and 1 and repeated $ninf$ times where $ninf$ = number of affected ecological patches, and $Eres$ is the ecological patch disturbance intrinsic resistance. Each ecological patch can be affected if and only if no treatment strategy is currently adopted (i.e. $A(S_i) = 0$ where S_i = social agent i connected to the ecological patch E_i). Once affected, ecological patches reduce the utility provided to social agents by eff (i.e. $y_t = y_{t-1} - eff$). However, if treatment is adopted, then ecological patches are able to recover the lost utility by rec (i.e. $y_t = y_{t-1} + rec$), up to the initial level ($= 100$).

2.3 Learning Strategies

If social agents are isolated (i.e. no knowledge exchange with other social agents), the only option is to rely on individual learning. The probability of adoption of a treatment strategy is then given by the following algorithm, that is based on the fact that a social agent will change strategies if they are dissatisfied with the current one (Schlag 1998):

- Si will average her payoff over the last mem time-steps (mem = memory of social agents).
- Si will check how many times a specific strategy (treatment or no treatment) has led to a payoff higher or equal than average payoff calculated in the previous step. NT_0 = number of times that a no-treatment strategy has led to higher than or equal to average payoffs; NT_1 = number of times that a treatment strategy has led to higher than or equal to average payoffs.
- Then, $pr0_i = \frac{NT_0}{NT_0+NT_1}$ and $pr1_i = 1 - pr0_i$: the probability of choosing strategy 0 increases linearly with the number of times that that strategy has led to better than average outcomes.

Social learning can be chosen only if social agents are connected to other social agents. Social agents can be either conformist imitators with probability $lprob$, or success-biased imitators with probability $1 - lprob$. If a social agent is a conformist imitator, he/she is able to see k neighbors and will choose with $pr0$ a specific strategy (treatment adoption vs no treatment adoption) depending on the number of neighbors that have adopted that strategy (as in (Henrich and Boyd 1998)):

- $pr0_i = \frac{n_0^{th}}{n_0^{th}+n_1^{th}}$ where th = exponent of the function that determines the gradient of the probability function (th = 1 corresponds to a linear increase in the probability of not adopting and $th > 8$ approximates a step function (see (Salau et al. 2012) for more details on this type of function used to determine probabilities). n_0 and n_1 represent the number of social neighbors that have not adopted (n_0) or adopted (n_1) treatment strategies.
- $pr1_i = 1 = pr0_i$ where $pr1_i$ = probability of adopting a treatment strategy.

If a social agent is a success-biased learner, he/she will be able to have full information of all payoffs and strategies of k neighboring agents. Adoption of a specific management strategy is given by the difference between the maximum payoff of neighbors and one's own (as in (Boyd and Richerson 1988)):

- $\Delta\pi = max(\pi_k) - \pi_i$ where $max(\pi_k)$= maximum payoff of neighbor's management strategy (treatment or no treatment) different than one's own. If all neighbors adopt the same strategy as one's own, than $\Delta\pi = 0$.
- The probability of switching to the strategy leading to the neighbor's maximum payoff equals $\frac{1}{1+\varepsilon^{-\Delta\pi}}$.

Social agents can switch between using individual and social learning if connected to other social agents (if isolated, they can only engage in individual learning). The choice between adopting individual *or* social learning depends on the clarity of strategy success and the social learning confidence level, reflecting the fact that social agents will switch learning strategies depending on their satisfaction level with the current one. Thus, at each time-step a social agent S_i:

- Checks the number of *mem* times a specific strategy (treatment or no treatment) has led to a payoff better than or equal to the payoff averaged over the last *mem* times. NT_0 = number of times that a no-treatment strategy has led to higher or equal than average payoffs; NT_1 = number of times that a treatment strategy has led to higher or equal than average payoffs.
- Each S_i calculates the clarity of winning strategy as $CW = abs(NT_1 - NT_0)$.
- If $CW = confid$, S_i will follow strategies dictated by individual learning, otherwise, it will follow strategies dictated by the social learning.

Finally, each social agent is prone to making mistakes due to either mis-interpreting the social and/or the ecological system. Such errors are represented by the probability *mu* of switching strategy.

2.3.1 Treatment adoption, eradication of ecological invasions and payoff

Social agents can either adopt treatment strategies ($A = 1$) or not adopt treatment strategies ($A = 0$). Adopting the treatment strategy either eradicates the ecological invasion or immunizes against ecological invasion. Treatment needs to be maintained, and if a social agent changes strategy to non-treatment ($A = 0$) then the ecological patch becomes susceptible to invasions.

Invasion of an ecological patch affects the utility of the social agent managing that patch and ultimately her payoff. More precisely, the payoff of a social agent (πS_i) is given by the utility derived by the ecological patch y and the decision to adopt treatment (with cost cls): $\pi_i = y_i - A \times cls$ where cls = cost of adopting strategy $A = 1$ (i.e. adopting treatment) and $y_t = y_{t-1}$ if the ecological node is not infected, or $y_t = y_{t-1} - eff$ if infected, where eff = effect of the ecological invasion on the utility provided by the ecological patch.

2.4 Lowess Smoothing

Locally weighted scatterplot smoothing (i.e. LOWESS smoothing) methods fit a low degree polynomial regression to a subset of the data derived from our simulations, hence showing non-linear trends between variables. The LOWESS method assigns increasingly higher weights to points closer to the the point where the dependent variable is estimated given the independent variable (Cleveland 1979, Cleveland and Devlin 1988) and as used in Baggio et al. (Baggio et al. 2011). The weights assigned follow a tricube function as follows: $w(x) = (1 - |x|^3)^3 for |x| < 1$ and $w(x) = 0 for |x| \geq 1$. Here we use lowess smoothing to assess the relationship between adoption and eradication time and between learning type and adoption, thus we truncate the smoother at 0 for eradication time and at 1 for adoption (as negative time values and greater than 100% adoption are nonsensical).

3 RESULTS

Our main objective is to understand the relationship between the adoption of treatment strategies that can eradicate ecological disturbances (e.g. treating fires, floods, agricultural pests and/or invasive species), the characteristics of the ecological disturbance (cost of treatment, possibility to recover, and effect), and learning.

The first step to disentangle the importance of social learning type and ecological disturbances is to understand the relationship between adoption of treatment strategy and the eradication of the ecological disturbance. As shown in Figure 2, adoption of the treatment strategy clearly increases the probability for the system to eliminate the effects of ecological disturbances. The more adoption occurs, the higher the likelihood that the disturbance is eradicated. However, it is also noticeable how the size of the overall system affects the actual threshold beyond which adoption always leads to eradication. More precisely, in the case of smaller systems ($Ne = Ns = 10$) if more than 30.4% of social agents adopt treatment, eradication is certain, while for bigger systems (i.e. $Ne = Ns = 100$) this threshold increases to 41.4%. Generally, the larger the system and the more complicated the coordination problem and the more difficult it is to eradicate ecological disturbances: more effort is needed to promote treatment strategies. Figure 2 also highlights the importance of social learning, more precisely of success-biased learning. Success-biased learning increases the odds of successful eradication. This is especially true, once again, for smaller systems where when more than 50.4% of social agents adopt a success bias, eradication is almost always assured.

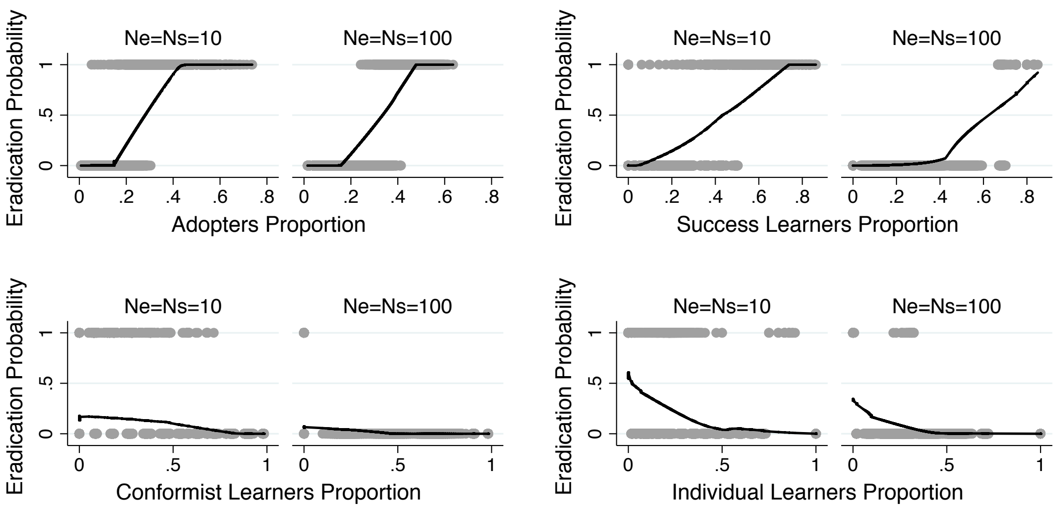

Figure 2: Relationship between eradication, adoption and learning. The solid line in each plot represents the trend in the data given by LOWESS smoothing. The figure shows the importance of adoption and the influence of success-biased imitation on the likelihood of ecological disturbance eradication.

As shown in Figure 2 adoption of the treatment strategy is fundamental to eradicate ecological disturbances. Adoption not only depends on learning type but also on: a) the ability of the system to recover if treated, b) the cost of treatment and c) the effect of ecological disturbances on the utility of social agents. Figure 3 displays these relationships by system size. Generally speaking, the number of adopters needs to be higher in order for eradication to occur (see also Figure 2). The difference is clear and independent of cost, effect and recovery ability of the ecological system once treated. Further, independent from system size, lower cost of treatment ($csl = 10$) and ability of the ecological system to recover ($rec = 10$) from the ecological disturbance once treatment starts increases the rate of eradication and the rate of treatment adoption. However, there is a fundamental difference relating to the effect of ecological disturbance on social agents' utility: in smaller system, intermediate, cumulative effects lead to a higher likelihood of eradication and higher rate of adoption (i.e. $eff = 50$) except when cost is low and recovery is possible ($csl = 10$ and $rec = 10$). On the other hand, in bigger systems, small, cumulative effects of ecological disturbances increase the likelihood of eradication and the rate of adoption ($eff = 10$). This difference indicates that in smaller systems it may be necessary for an ecological disturbance to be clearly visible and have a strong and fast effect on manager's utility in order for them to act to treat the disturbance. However, when systems increase in size, a sizable effect is detrimental to eradication and adoption of treatment strategies. While this is an interesting result, it can be truly uncovered only by a rigorous qualitative analysis and research on motivation of managers to adopt specific treatment strategies.

Further, the characteristics of ecological disturbances (recovery, cost and effect) also influence social agents decision with respect to learning. The type of learning strategy adopted by social agents is a fundamental determinant of the system's ability to eradicate ecological disturbances. Imitating successful social agents, under the assumption that all agents have the same objective, that ecological disturbances affect utility homogeneously and that agents have full information (i.e. a social agent is aware of strategies and utility of all other social agents in the system) increases the likelihood of eradication. Figure 4

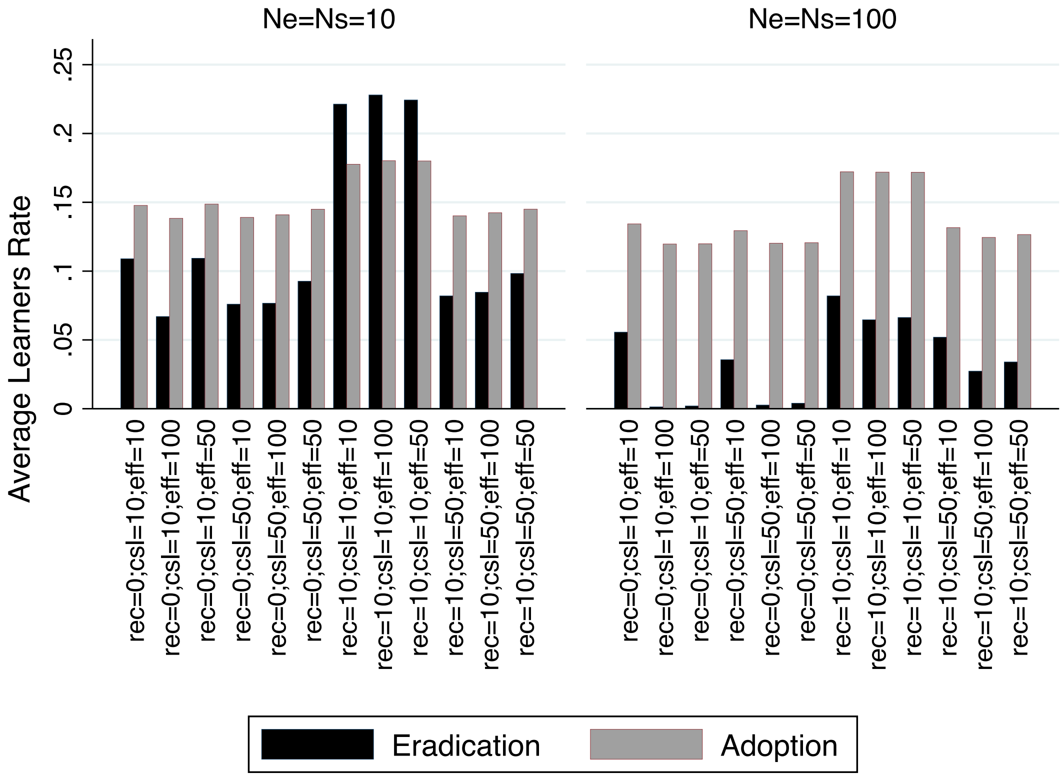

Figure 3: Relationship between eradication of ecological disturbance, adoption, treatment cost, utility recovery once treatment is administered, and effect of the ecological disturbance on utility by size of the system (Ns=Ne= 10 vs Ns=Ne=100).

disentangles the relationship between learning, ecological disturbances, system size, and eradication. From Figure 4 we can infer that the type of ecological disturbance influences the type of learning, especially in the case of low cost and possibility of recovery in smaller systems ($csl = 10$, $csl = 10$, in $Ne = Ns = 10$). In smaller social-ecological systems, specific characteristics of the ecological disturbance do not affect the importance of success-biased learners in increasing the likelihood of eradication. However, the importance of low cost of treatment and the ability for the system to recover are clearly important in determining successful eradication when social agents are not success-biased imitators but rely on individual learning or conformity. On the other hand, in larger systems specific characteristics do not affect the relationship between learning type and eradication, except when $csl = 10$, $rec = 10$ and $eff = 50$ or 100. In this latter case, the rate of eradication increases for individual learners, while the rate of persistence of the ecological disturbance increases in the case of success-biased learners.

In the case of disturbance persistence (grey bars in Figure 4) most social agents adopt an individual learning strategy (i.e. $> 50\%$). On the other hand, when eradication is successful, the majority of social agents not only adopt social learning as a preferred learning strategy, but most employ success-biased imitation (i.e. 60% in all cases). Success-biased imitation is a key component of the ability of a social-ecological system to manage and eradicate ecological disturbances.

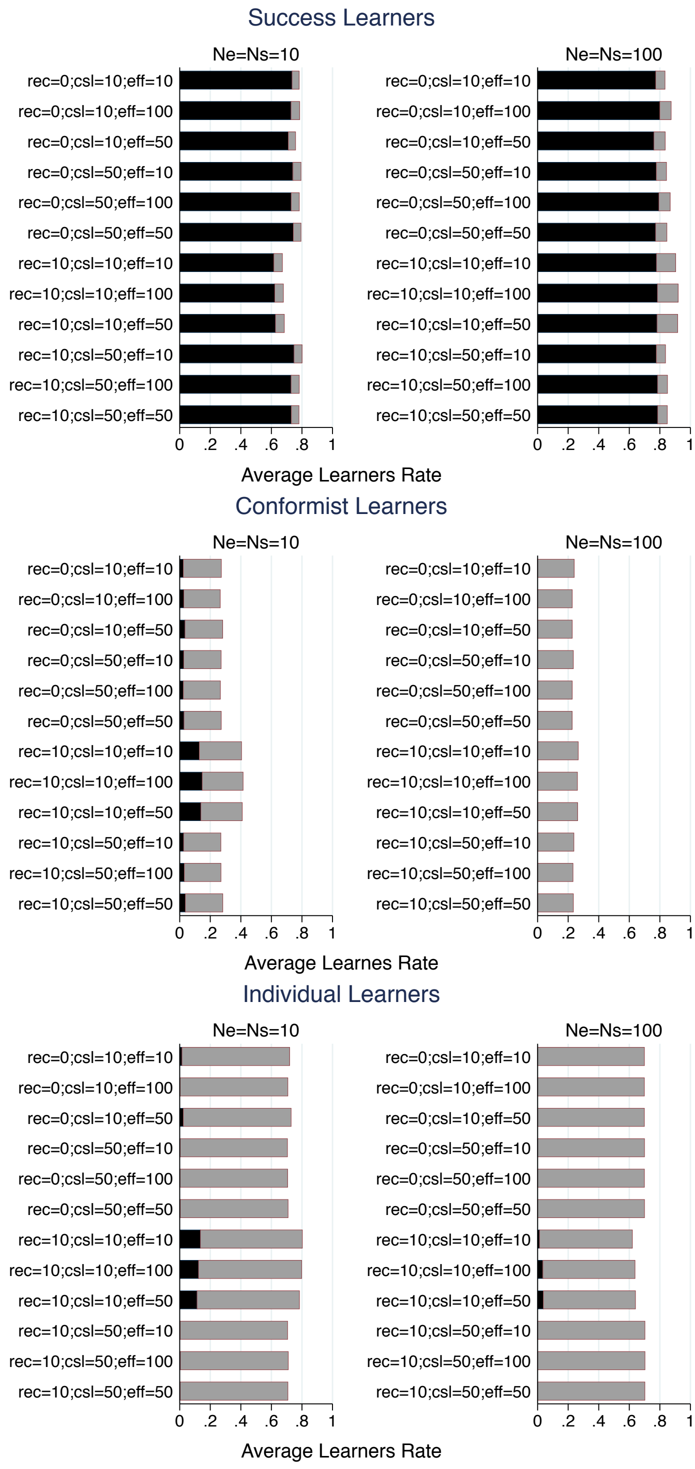

Figure 4: Relationship between learning type, cost of treatment, treatment cost, utility recovery once treatment is administered, and effect of the ecological disturbance on utility by size of the system (Ns=Ne= 10 vs Ns=Ne=100). Black bars = Learners rate in case of ecological disturbance eradication; Grey bars = Learners rate in case of persistence of the ecological disturbance in the system.

4 CONCLUSION

Ecological disturbances (i.e. fires, floods, pests, invasive species etc.) affect our well being and are a fundamental challenge in our increasingly connected world (Pimentel 2011). Hence it is crucial to understand how social agents that have the authority to manage specific patches of the landscape make decisions and how these decisions affect the wider social-ecological system. Using an agent based model in which social agents can use various learning strategies, coupled with an underlying connected ecological system that is affected by ecological disturbances, we explored the relationship between treatment adoption, learning, and ecological disturbances.

Generally, managers adopt practices that result in a relative advantage over other alternatives (Rogers 2003, Ghadim and Pannell 1999). However, in a highly connected world, individual learning based on trial and error is not sufficient to counter complex problems such as ecological disturbances in fragmented landscapes (Giraldeau and Beauchamp 1999). Our model reinforces this conclusion but also demonstrates the costs of conformity. In fact, success-biased imitation is preferable, under the right conditions. For example, our model shows that success-biased imitation is the learning strategy that most increases the likelihood to eradicate invasions. However, this is based on the premise that social agents have full information on strategies and utility derived by the ecological system of all other agents and that all agents actually have the same relationship between the ecological system and their own utility. Despite these caveats, success-biased imitation is also shown empirically to be preferred to conformity when individual engage in social learning (McElreath et al. 2008, Mesoudi 2011).

This study is just the beginning of a promising line of research. Here we demonstrate the importance of social learning, under specific assumptions that we aim to relax in the future. For example, how do different types of learning strategies perform when the system is partially connected? What is the relationship between the structural properties of the social and ecological system (i.e. the underlying social-ecological network), learning strategies, treatment adoption and eradication of ecological invasions?

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