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Managing ecological disturbances: Learning and the structure of social-ecological networks

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ABSTRACT

Ecological disturbances (i.e. pests, fires, floods, biological invasions, etc.) are a critical challenge for natural resource managers. Land managers play a key role in altering the rate and extent of disturbance propagation. Ecological disturbances propagate across the landscape, while management strategies propagate across social networks of managers. Here we use an agent-based model to examine the joint diffusion of ecological disturbances and management strategies across a social-ecological network, accounting for the fundamental role of social-ecological feedbacks. We examine the management of a generic ecological disturbance as a function of different learning strategies and the social-ecological network. Our approach provides a general scaffold that can be modified to examine a variety of processes in which both social and ecological flows propagate across a social-ecological network. Our findings highlight the importance of full and accurate information to assess successful strategy, limited clustering and alignment between the social and the ecological system.

1. Introduction

Ecological disturbances, defined broadly to include invasive species, agricultural pests, fires, floods, urbanization and land use change, affect biodiversity and are a fundamental challenge in our interconnected and fast-changing world (Chapin, 2009; Pimentel, 2011). The decisions of land managers play an important role in constraining or promoting the spread of these disturbances (Baird et al., 2016). Management decisions spread across an informational network via learning while ecological disturbances spread across the landscape. While much research has examined these two processes in isolation, relatively little has explored the simultaneous propagation of a disturbance and the management of that disturbance across a linked social-ecological network (Rebaudo and Dangles, 2011, 2015). Yet examining these processes in isolation misses the important role of reciprocal feedbacks in these complex systems. In this paper, we propose to integrate the analysis of social-ecological networks using the tools developed to analyze multiplex networks, and agent based models designed to capture the fundamental characteristics of the decision-making process as well as the ecological disturbance and the feedbacks between the two.

In general, managers adopt practices that they view as better than available alternatives (Rogers, 2003). Managers can compare strategies using experiential, or individual, learning, in which they conduct trials of different strategies and observe the results to inform their future decisions (Ghadim and Pannelli, 1999). Individual learning, however, is constrained when outcomes are difficult to observe or delayed over long periods (as is the case, for example, in perennial cropping systems or with catastrophic events that occur very infrequently), or if the results from individual learning are unproductive (Giraldeau and Beauchamp, 1999). Given the challenges of relying exclusively on individual learning, managers also employ social learning: they seek out and use information from peers (Baird et al., 2016; Isaac et al., 2007).

Especially when unsatisfied with current strategies (Schlag, 1998), when constrained by authority, or when outcome uncertainty is high (Morgan et al., 2012), managers rely on information transmitted through social networks to shape their decision making (Baggio and Hillis, 2016; Baumgart-Getz et al., 2012; Bodin and Crona, 2009; Bodin and Tengö, 2012; Crona and Bodin, 2006; Cumming, 2016; Kininmonth et al., 2015; Prokopy, 2011). Managers acquire knowledge via peer-to-peer interactions, local and regional organizations, or other managers with greater authority. While formal or legal authority constrain decision making in important ways, informal social networks are also critical, particularly across fragmented jurisdictions or when formal power dynamics are less prominent (Cumming, 2016; Kininmonth et al., 2015). Managers learn socially from network neighbors using various strategies (Collins, 2005; Laland, 2004). Two important strategies

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include 1) a success bias, where individuals preferentially copy the strategies of other successful individuals (Boyd and Richerson, 1988; Schlag, 1998), and 2) a conformist bias, in which individuals are disproportionately likely to adopt the most common strategy within a population, independent of the actual success of that strategy (Henrich and Boyd, 1998).

Some ecological disturbances are easily observable and their effects are immediate (e.g. fires, and floods). However, sometimes disturbances can be hard to detect and their effects can be cumulative yet catastrophic (Chades et al., 2008; Chadès et al., 2011; MacKenzie et al., 2002). The management of ecological disturbances is further complicated by increased ecological and social fragmentation (Epanchin-Niell et al., 2010; Rebaudo and Dangles, 2011; Sayles and Baggio, 2017a; Schoon et al., 2014). Due to the fact that ecological processes often unfold at a different spatial scale than social processes, efficient management requires adoption of strategies at the appropriate ecological scale (Ager et al., 2017; Crowder et al., 2006; Cumming et al., 2006; Folke et al., 2007; Galaz et al., 2008; Sayles and Baggio, 2017b).

Given the complexity of managing ecological disturbances, empirical research can be productively complemented with computational models that explicitly couple social and ecological networks, thereby examining the simultaneous diffusion of ecological disturbances and the strategies used to manage them. This endeavor can benefit from the combined use of network theoretical tools, agent based modeling, and specific case studies that can illustrate and guide the dynamics presented in models. A number of recent studies have examined transmission across networks connected via multiple types of relationship (i.e. multiplex networks), and the robustness of such multiplex networks to social and ecological perturbations (Baggio et al., 2016; De Domenico et al., 2016; Lima et al., 2015). Agent based models (ABMs) have been increasingly applied in social and ecological systems (DeAngelis and Mooij, 2005; Fischer et al., 2013; Rebaudo and Dangles, 2015), uncovering emergent properties of systems represented from the bottom-up by agent behavior. Here we propose an integration of concepts relating to multiplex networks and agent based models in order to more realistically portray decision-making processes on fragmented social-ecological landscapes. Our analysis is designed to capture the important characteristics of both social and ecological processes of diffusion across a landscape, allowing us to assess the influence of network structural properties on a generic disturbance. While our model is highly abstract, the general approach can be modified to more realistically apply to any number of processes in which multiple flows diffuse across a multiplex network.

We examine the management of ecological disturbances as a function of learning, and the disturbance itself, on a social-ecological network. Our study aims to provide some theoretical insight into the relationship between learning on social networks and ecological disturbances propagating on a landscape. We build an ABM in which managers can adopt strategies to counter ecological disturbances at a specific cost. Managers make decisions based on information they acquire via individual or social learning, through feedbacks from the ecological patch they are managing. We proceed by first explaining the model in detail. We then highlight our results, providing insights into the relationship between network connectivity, learning type and disturbance management. The discussion and conclusion of the paper focus on these relationships within the wider context of ecological disturbances. While we consider the primary contribution of this work to be developing a methodological approach for the study of coupled social-ecological systems using an approach integrating agent-based modeling and network analysis, in the discussion we also highlight the importance of extending these findings, that use an idealized landscape, to real-world management practices and data.

2. Methods

In order to assess the relationship between social-ecological network structure, the spread of ecological disturbances and the adoption of management strategies, we developed an agent based model comprised of N connected social and ecological agents (i.e. a social-ecological network). Social agents are able to adopt treatment strategies that stop the spread of the disturbance and cure affected ecological patches. Each social agent has the authority to manage, exclusively, one ecological patch. Ecological disturbances can propagate through the ecological landscape. The model, however, can be easily extended to assess situations in which social agents are able to manage multiple ecological patches, as well as cases in which multiple social agents are managing the same ecological patch.

2.1. The ecological system

We specify the ecological landscape as an unweighted and undirected network in which $N_e = 100$ patches (i.e. ecological nodes) are connected via geoproximity. The ecological nodes are scattered randomly on a 2-Dimensional grid. Edges are added, connecting each pair of most closely-connected edges first (where closest refers to the Euclidean distance between the patches on the grid), until the pre-defined number of edges, $E_{ee,}$ is reached, as described (Baggio et al., 2011). All patches are assigned a base utility (y) and at the beginning of each simulation 10% of patches are considered affected by a generic ecological disturbance. The disturbance can propagate via edges that link the ecological patches. Patches can be either treated or untreated. Treated patches are protected from the disturbance while untreated patches always become disturbed if neighboring patches are disturbed. In other words, an ecological patch becomes disturbed if it is connected to a disturbed ecological patch and it is not treated. Once disturbed, the utility of that patch decreases at each time-step by a specific amount (see supplementary material, Table S2 input values).

2.2. The social system

Social agents are connected via an unweighted, undirected network and represent $N_s = 100$ social nodes. More specifically, social agents are connected via 6 different network generating processes: a) matching the ecological connectivity (scale match), b) randomly, c) representing a small world with rewiring probability (i.e. $p_{rew} = 0.2$) or d) small world with rewiring probability ($p_{rew} = 0.3$), e) representing a scale free network with low preferential attachment ($p_{pref} = 0.6$) or f) a scale free network representing high preferential attachment ($p_{pref} = 1$) (see also Figure S7).

Each social agent is able to exclusively manage one patch. Agents are able to adopt a treatment at a specific cost. Agents make their adoption based on their payoff, the type of learning they employ, the feedback from the ecological patch they are managing, and the information they acquire from their social network. Further, each agent can misinterpret signals (or commit judgment errors) and adopt either strategy with probability *mu*.

Payoff is given by utility (affected by the ecological disturbance) and whether a manager has adopted treatment or not: $\pi_{i,t} = y_i - A_i{*}cls$ where cls = cost of adopting treatment, A indicates whether treatment has been adopted or not, and $y_t = y_{t-1}$ if the ecological node is not disturbed, and $y_t = y_{t-1} - eff$ if the ecological node is disturbed where eff = effect of disturbance on utility (see supplementary material for the actual values used in the simulations).

Agents employ either individual or social learning, and can switch between the two types of learning. When agents employ social learning, they are either conformists (they adopt the strategy adopted by the majority of their social neighbors) or success-biased imitators (they adopt the strategy of the individual neighbor that is doing best). Agents use either conformist or success-biased social learning; they are not able to switch between the two.

Agents who are socially isolated (i.e. have no social connections) always employ individual learning, and adopt treatment using the following algorithm:

1. An agent (S_i) will average her payoff over the last *mem* time-steps (where *mem* = memory of social agents).
2. S_i will check how many times a specific strategy (treatment adoption –NT_1– or no treatment adoption –NT_0) has led to a payoff better or equal to the average payoff calculated in the previous step.
3. The probability of choosing no treatment adoption ($pr0_i$) is given by the following equation: $pr0_i = \frac{NT_0}{NT_0 + NT_1}$, hence the probability of treatment adoption is $pr1_i = 1 - pr0_i$.

If agents are connected to other agents via the social network, they have the ability to choose whether they will learn individually or socially. The choice between individual or social learning depends on the clarity of strategy success and the inherent preference of agents for individual or social learning, as explained in the following algorithm:

1. S_i checks the number of *mem* times a specific strategy (treatment adoption or no treatment adoption) has led to a better or equal payoff compared to the average payoff calculated over the last *mem* times.
2. Each S_i calculates if there is a clear winning strategy $CW = \text{abs}(NT_1 - NT_0)$, where NT_1 = number of times treatment was successful, and NT_0 = number of times not using the treatment was successful.
3. If $CW \geq$ threshold given by social agent preference for individual vs social learning (i.e. parameter *confid*) S_i will employ individual learning, otherwise, it will use social learning.

If an agent uses social learning they can either employ success or conformist-biased learning. Success-biased learners will assess the payoffs and management strategies of k neighboring agents. Treatment adoption is then a function of the difference between the maximum payoff of the k neighbors and ones' own payoff ($\Delta\pi$): $\Delta\pi = \max(\pi_k) - \pi_i$ where $\max(\pi_k)$ = maximum payoff of neighbors. If all neighbors adopt the same strategy as ones' own, than $\Delta\pi = 0$. The probability of switching to the strategy leading to the maximum payoff between neighbors equals to $1/1 + e^{-\Delta\pi}$.

Conformist learners assess the strategies of k neighbors and choose not to treat their patch with probability *pr0,* which is a function of the number of neighbors that are not treating: $pr0_i = \frac{n_0^{th}}{n_0^{th} + n_1^{th}}$ 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 $th > 8$ simulates a step function (see Salau et al. (2012) for details on the role of the parameter *th*)); n_0 and n_1 represent the number of social neighbors that have not adopted (n_0) or adopted (n_1) treatment. Finally, adoption of strategy ($pr1_i$) is given by $1 - pr0_i$.

Feedbacks between the social and ecological systems occur in the form of general utility that a social agent receives from the ecological patch they are managing. If the patch is disturbed, their utility is reduced. Social agents tend to want to keep the level of utility or to increase it.

The ability of a system to successfully manage a disturbance is assessed here by analyzing the average percentage of individuals employing a specific type of learning during the course of the simulation run, the percentage of individuals adopting treatment in the 100 time-steps preceding the end of the simulation run and in the percentage of ecological patches that are disturbed when eradication does not occur. For an in-depth description of the model and the parameter values used in simulations, please see the Overview Design and Detail protocol (ODD) (Grimm et al., 2010, 2006) presented in the Supplementary Material. The model code and the ODD are also available at https://www.comses.net/codebases/5502/releases/1.1.0/.

2.3. Social-ecological network analysis – multiplex networks

The relationship between structural properties of the underlying social-ecological system, adoption and eradication is assessed via multiplex network metrics. To analyze the social-ecological network as a multiplex network we need to consider the *Ns* and *Ne* agents as one single group of agents (*Nse*) that are connected via two different types of edges, social and ecological. The ensemble of the social connections between the *Nse* agents thus forms the social layer, while the ensemble of ecological connections between the *Nse* agents forms the ecological layer of the multiplex network. We can analyze multiplex networks by calculating the adjacency tensor of the social-ecological network (SEN). The adjacency tensor can be thought of as a multi-dimensional array. For example, a two-dimensional array can be represented by a matrix where one needs to specify two indices (i and j) to uniquely identify an edge (i.e. the matrix is a specific case of a rank-2 tensor). To uniquely identify an edge in a multiplex network, one needs to specify four different indices, two to identify involved nodes and two to identify the involved layers: the edge between node i in layer s and node j in layer e is uniquely identified in a rank-4 tensor, whose components are indicated as $M_{i,j}^{s,e}$ (Baggio et al., 2016; De Domenico et al., 2013; Kivelä et al., 2014; Mucha et al., 2010). Here we analyze four specific multiplex network metrics that reveal the structure of the underlying social-ecological system: average degree, average local clustering coefficient, global clustering coefficient, and inter-layer correlation.

2.3.1. Multiplex average degree

The multiplex degree (Mpx Degree) identifies the average potential for social learning and propagation of ecological disturbances. The multiplex degree is a result of the combination of social and ecological connectivity.

The average multiplex degree of node i is calculated as the average degree of node i in each layer (here s = social layer and e = ecological layer), $k_i = \{k_i^s, k_i^e\}$ and diviced by divided by *Nse* (De Domenico et al., 2013).

2.3.2. Multiplex clustering coefficient

The multiplex clustering coefficient identifies the potential for the network to receive localized information from the ecological layer and the potential for learning based on neighboring nodes in the social layer. Here we assume that the ability of information and disturbance signals have the same possibility of remaining within the same layer or crossing layers.

Following Cozzo et al. (2015) we calculate the global clustering coefficient (Mpx Global CC) and the average local clustering coefficient (Mpx Local CC) based on random walks where the probability of changing layers is equal to 0.5 (thus signals have the same probability of crossing or remaining in the same layer). It is important to notice that while the average local clustering coefficient, by construct, places more emphasis on low multiplex degree nodes, the global clustering coefficient puts more emphasis on nodes with high multiplex degree.

2.3.3. Inter layer assortativity

The inter-layer assortativity can be calculated as the inter-layer correlation of the node degrees of the two layers. Assortativity identifies the relationship between the potential for propagation of the ecological disturbances and the potential for adoption of strategies via social learning. Assortativity is a key property of multiplex networks (Nicosia and Latora, 2015). Here we employ Spearman pairwise correlation to assess the correlation between the degree of a node in the social layer and its degree in the ecological layer. Formally, we calculate the inter-layer correlation as follows (see also Baggio et al., 2016):

$$\rho_{s,e}(pq) = 1 - \frac{6\sum_{i=1}^{N}[r_i^s(p) - r_i^e(q)]}{N(N^2 - 1)}$$

where p, q = node degree and r_i^s is the rank of node i in layer s (see De Domenico et al., 2013 for in depth information on multiplex metrics).

2.4. Analyzing model output

The model assesses ecological disturbances as a function of learning and the structural properties of the underlying social-ecological network. To analyze the complex interactions between learning, disturbance, and structural properties of the network we evaluate the effect of various model parameters by statistically analyzing our model output. Given that disturbance prevalence lies in the [0,1] interval, where both 0 and 1 have a positive probability to be an actual outcome, we follow Papke and Wooldrige (Papke and Wooldridge, 1996) and analyze the results via the following equation: $E(y|x) = f\left(\overrightarrow{\beta x}\right)$ estimated via quasi-maximum-likelihood methods as explained in (Gourieroux et al., 2016). Here, $E(y|x)$ is the expected prevalence of ecological disturbance (expected disturbance), $\overrightarrow{\beta x}$ is a vector of model variables as parameterized (see input table in the supplementary material) and $f(\cdot)$ represents a logistic function: $f(g) = {}^{e^g}\!/_{(1+e^g)}$. The model variables analyzed are: proportions of success-biased, conformist, and individual learners, multiplex global clustering coefficient, multiplex local clustering coefficient and assortativity. We interact learner types (2 at a time to avoid perfect multicollinearity, as the sum of the proportion of success-biased, conformist and individual learners = 1) and multiplex network metrics in order to assess the relative importance of each model variable. We assess average marginal effects of learning type frequency and network metrics in order to assess how their main effect on expected disturbance changes due to their interactions.

3. Results

Our main objective was to understand the relationship between adoption of treatment strategies, learning, social-ecological networks, and expected disturbance in the overall system. There is a clear link between adoption and eradication of ecological disturbances. On average, adoption of treatment strategies is almost three times higher (≅2.8) when the disturbance is eradicated than when it is not (Table 1). Treatment of disturbances and their eradication is a clear-cut relationship. However, expected disturbance also depends, directly and indirectly, on learning types and the underlying structural properties of the social-ecological network.

The results portrayed below graphically display the relationship between learning and expected disturbance, as well as social-ecological network metrics and expected disturbance. In Table S1 we report the parameter estimates for three models examining the network metrics and interactions between success-biased and conformist learners (SC), success-biased and individual learners (SI), and conformist and individual learners (CI). Figure S1 to S3 report further analysis of the pairwise relationship between interacting variables and their effect on expected disturbances (i.e. how the coefficient changes). Following we report how expected disturbance prevalence changes depending on learning and structural properties of the social-ecological network. We report results for the SC model (SI when individual learners are involved) as there is no qualitative difference in the multiplex metrics interactions between the three models (see Figure S4 and S5).

Table 1
Eradication and adoption.

Expected Disturbance = 0: Eradication	Treatment Adoption		
	mean	median	std.
No	0.165	0.144	0.126
Yes	0.367	0.404	0.199

3.1. Learning

As the proportion of success-biased learners approaches 1, expected disturbance decreases (i.e. when > 90% of the agents employ success-biased learning, on average, expected disturbance ≅ 0.25). On the other hand, if conformist learners or individual learners represent more than 60% of the population, on average, expected disturbance ≅ [0.70, 0.64] *or* [0.70, 0.48] depending on the increased number of conformist or individual learners respectively (Fig. 1a and b). Fig. 1c reiterates the importance of success-biased learners as expected disturbance is minimized when both the proportions of conformist and individual learners are < 0.1.

3.2. Social-ecological networks

The relationship between the structural properties of the underlying social-ecological network and the ability of the system to reduce the ecological disturbance is dependent on the general connectivity of the overall social-ecological network, how it is clustered and whether the social and the ecological layer display inter-layer assortativity. On average, increases in average multiplex degree reduce expected disturbance (Fig. 2a, b, and 2d). On the other hand, increased clustering, in particular local clustering, increases expected disturbance (Fig. 2a, b, 2c, 2e, 2f).

The difference between multiplex global and local clustering is better observed together with multiplex degree (Fig. 2a and b). A minimum level of global clustering is necessary for lowering expected disturbance. In fact, if global clustering is < 0.15, expected disturbance is expected to be around 0.5. Further reduction occurs when global clustering increases. Local clustering always increases expected disturbance. Fig. 2b clearly shows that as local clustering increases, expected disturbance also increases. At high levels of local clustering, degree only reduces expected disturbance if it is very high.

Fig. 1 and Fig. 2 highlight the importance of success-biased learners (Fig. 1a and b) and increased levels of average multiplex degree (Fig. 2a, b and 2c) and assortativity (2d, 2e,and 2f) for reducing expected disturbance. On the other hand, we have observed how individual and conformist learners (Fig. 1), as well as local clustering constrain the reduction of expected disturbance (Fig. 2f, b and 2c). At the same time, while global clustering has a negligible effect at higher degree levels (Fig. 2a), it clearly influences the effect of assortativity (Fig. 2e).

3.3. Learning and social ecological networks

Given the results so far, it is important to disentangle the effect of learning and social-ecological network metrics on expected disturbance.

An increased frequency of success-biased learners (Fig. 3a–d) is associated with a reduction in expected disturbance. Further, a higher proportion of success-biased learners decreases the need for higher average multiplex degree, or assortativity (Fig. 3a and d). However, success-biased learners are negatively affected by global and local clustering. In fact, clustering reduces the effect that success-biased learners have on reducing expected disturbance (Fig. 3b and c). Conformist learners, however, do not have a strong effect on disease prevalence. Across changes in proportions of conformist learners, the main drivers of expected disturbance are the social-ecological network metrics (Fig. 3e through h). We find similar patterns for individual learners (Fig. 3i through l), with some important exceptions. Individual learners benefit from increases in local clustering, and are negatively affected by increases in assortativity. Individual learners, thus, seem to reduce expected disturbance at higher levels of clustering and lower levels of scale matching across the social and ecological sub-systems.

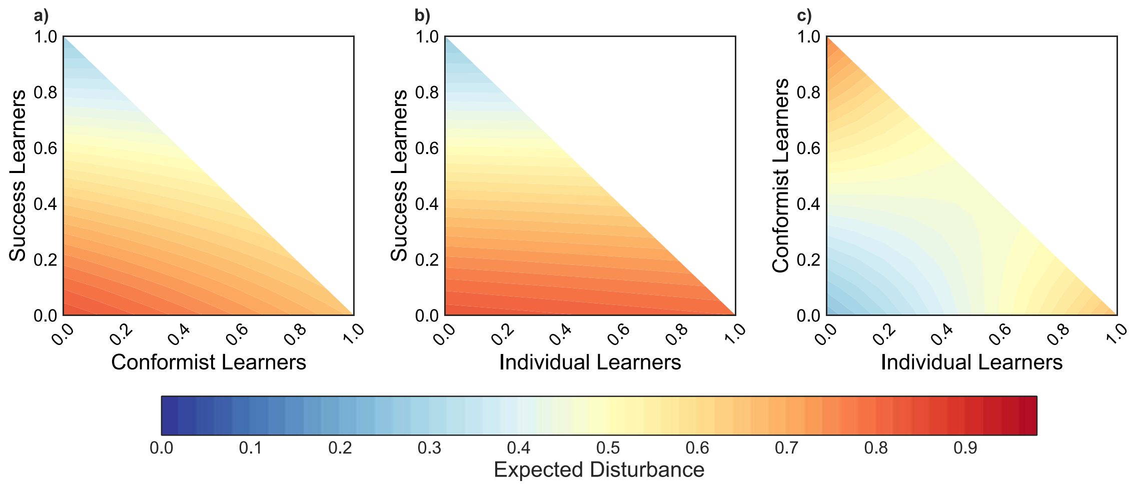

Fig. 1. Expected ecological disturbance prevalence as a function of frequency of learner types. Success-biased learners reduce disturbance. Both conformist and individual learners, on average, increase expected disturbance.

4. Discussion

When managers adopt the treatment, they eliminate the disturbance in the area they are managing, thereby decreasing the probability of transmission and reducing the overall prevalence of the ecological disturbance. While straightforward, this result highlights the importance of understanding the structural and institutional conditions that promote action on the part of managers. Our model allows us to examine the network structures and learning strategies that promote adoption.

Success-biased learners are critical for the reduction of ecological disturbances. However, this depends on agents being able to access more information than any other type of learner. While all agents have information about their own behavior and payoffs, conformist learners also have information about the behaviors of other individuals in their network, and success-biased learners have information about both the behaviors *and* payoffs of other individuals in their network. Interestingly, the additional information about others' behaviors

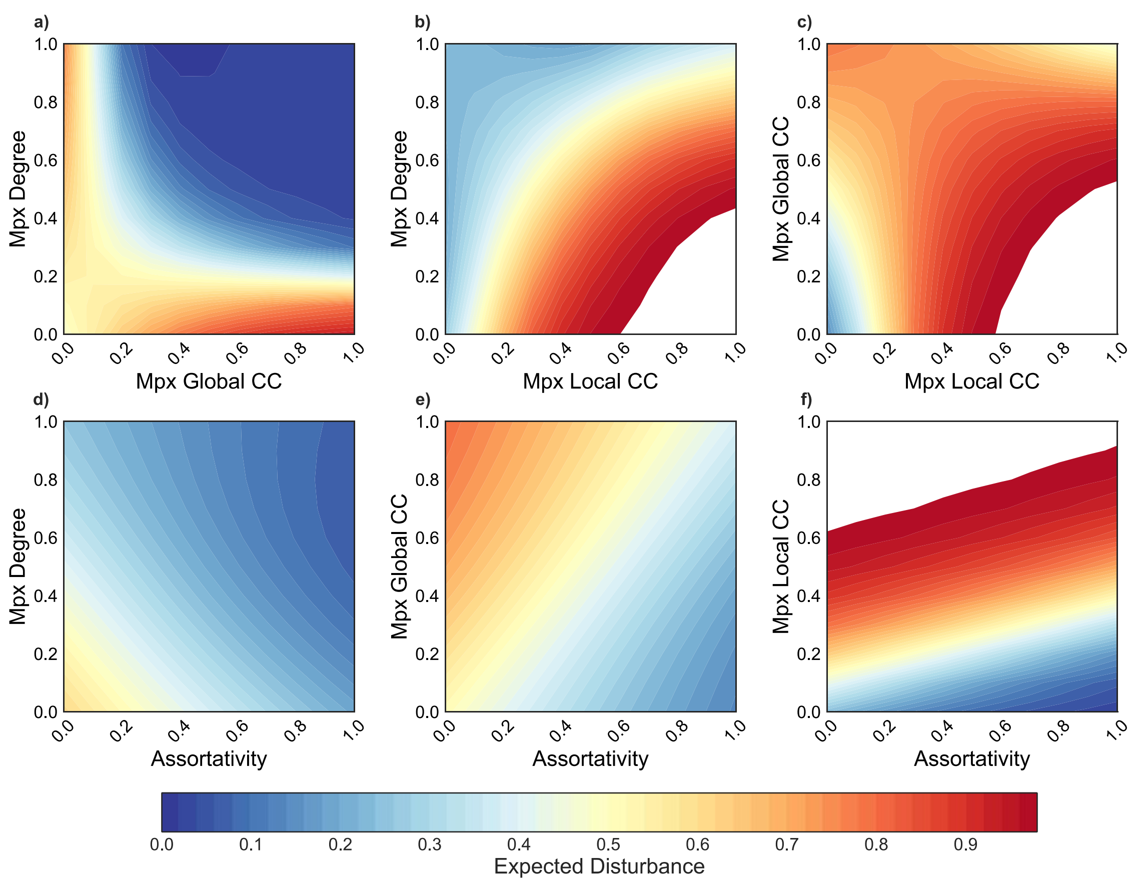

Fig. 2. Structural properties and expected ecological disturbance prevalence. While an increase in multiplex degree and assortativity reduce expected disturbance, increases in global and local clustering increase disturbance. White areas are for non-defined value combinations of the structural properties.

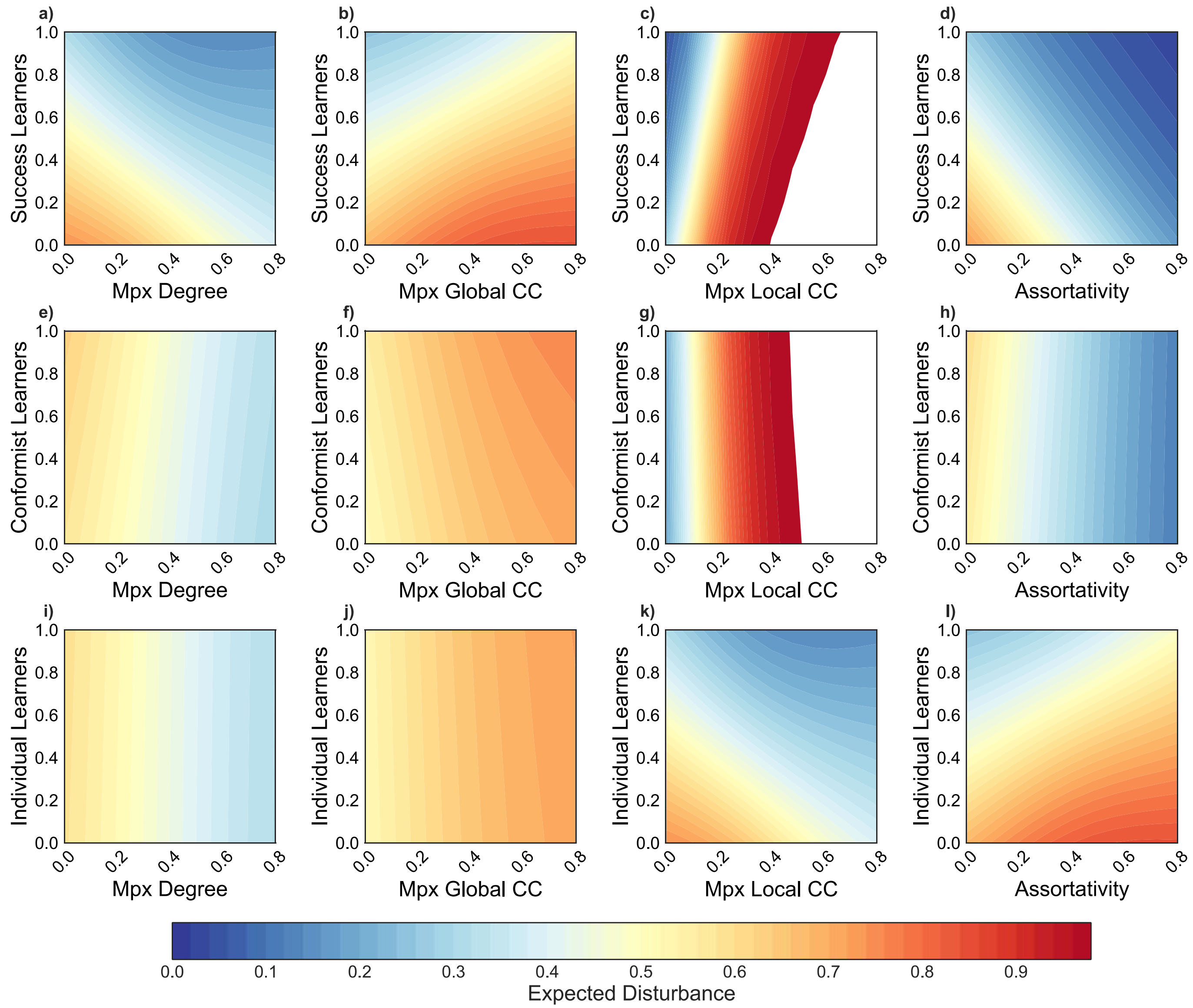

Fig. 3. Interactions between learning types and structural properties and their effect on expected disturbance. Success-biased learners, together with assortativity and multiplex degree reduces expected disturbance. Clustering increases expected disturbance. However local clustering in the presence of individual learners actually reduces expected disturbance.

actually harms conformist learners in that they are less able to control ecological disturbances. Conversely, the additional information improves the decisions of success-biased learners. This finding is consistent with theoretical expectations that predict a mix of conformity and success-biased learning produces adaptive outcomes (Boyd and Richerson, 1988). Conformity alone, however, can lead to systematic maladaptation with groups of individuals converging on the wrong behavioral outcome. These findings are also consistent with empirical evidence that individuals use success-biased learning to guide their own behavioral decisions in the real world. For example, experiments have shown that people employ success-biased and conformist learning strategies, as predicted, but that a success bias is often preferred to conformity and leads to better outcomes (McElreath et al., 2008; Mesoudi, 2011; Morgan et al., 2012).

The structure of the underlying social-ecological network influences disturbance prevalence in important ways. Specifically, increased assortativity, associated with social-ecological scale match, multiplex degree and global clustering all result in reduced disturbance prevalence. On the other hand, local clustering increases the prevalence of ecological disturbances. The important role of aligning structures across the social and ecological sub-systems is well known (Bodin et al., 2016; Sayles and Baggio, 2017a; Treml et al., 2015). Our results reiterate that when the connectivity of the social system adequately reflects that of the ecological system, ecological disturbances can be reduced and eradicated. However, scale matching alone is not sufficient for effective management; the overall connectivity of the system is also important, as shown by the relationship between multiplex global clustering, average degree and disturbance levels.

On the other hand, local clustering hinders the system's ability to reduce disturbances. The role of local clustering is related to the existence of close knit communities, and in the case of a multiplex network, is related to a redundancy in information sharing and probability of disturbance propagation, hence why local clustering increases disturbance prevalence. (Bodin, 2017). According to our findings, close knit communities, redundancy in information sharing, and scale mismatches provide conditions in which individual learning can reduce ecological disturbances. We can speculate that managers are better off trying new strategies when knowledge is redundant due to the closeness of the community.

This interaction between social-ecological connectivity and learning strategy is an important area of potential further exploration. For example, Hillis et al. (2017) posit that in the preventive management of trunk diseases among perennial crop farmers, an inability to engage in success-biased learning limits the adoption of preventive disease controls. The reason for the inability lies in the long latent period (several years) between infection and symptom expression in the trunk disease complex. This latent period effectively disassociates plant health from management behavior, at least temporarily, in the sense that farmers who are not preventively managing their vines may still have productive yields. The mismatch in temporal scales at which ecological mechanisms and management actions unfold prevents farmers from effectively engaging in a success bias by observing both the payoffs and strategies of their neighbors. Consequently, this real-world system exhibits high rates of ecological disturbance (Hillis et al., 2016), analogous to our model findings when farmers are unable to correctly imitate successful strategies.

Our findings generate a number of insights that inform outreach and policy intended to promote action on the part of land managers. The model underscores the importance of the structural properties of the social-ecological system. Because degrees of ecological connectivity vary substantially across disturbance types and ecosystems, understanding the social structures and learning strategies best suited to promote effective management in that ecological setting is critical. In other words, understanding the relationship between social-ecological connectivity and learning is key to promoting effective management strategies that can control ecological disturbances. These results underscore the importance of promoting social connections among individuals, with the important caveat that connections in and of themselves are not necessarily enough to promote appropriate action (Valente, 2012). Connections that allow for success-biased imitation, or those that allow individuals to observe both the behavior and payoffs of their decisions, are most likely to effectively promote adoption.

Policies that promote the sharing of information about both behaviors and their consequences are more likely to be effective than those that share merely information about the most common strategies. This type of information sharing, often the result of collaborative approaches, can be a challenge in environments that are inherently competitive, such as in the case of firms competing in a particular industry. As a substitute for or complement to facilitating success-biased learning, decision-makers might reduce the clustering of the overall system, by reducing ecological connectivity, and at the same time improve alignments in spatial scale such that highly connected ecological areas are managed by highly connected managers.

5. Conclusion

There has been considerable progress in the past few years in understanding dynamic processes on multiplex networks and the robustness of multiplex networks to specific disturbances (Baggio et al., 2016; De Domenico et al., 2014; Granell et al., 2013; Lima et al., 2015). Most studies addressing structural properties of social-ecological systems focus either on understanding how social networks (or their origin) influence the management and policies affecting the ecological system (Berardo and Scholz, 2010; Bodin et al., 2006; Lubell et al., 2014; Sayles and Baggio, 2017b; Schoon et al., 2017; Vignola et al., 2013), or employ a network perspective to examine and identify spatial scale mismatches existing in social-ecological systems (Ernstson et al., 2010; Guerrero et al., 2013; Sayles and Baggio, 2017a; Treml et al., 2015). Research on how social-ecological network structural properties influence the ability of social-ecological systems to adapt and transform is still in its infancy (Bodin, 2017).

Here we developed an agent based model to address the relationship between learning, social-ecological structural properties and the adoption of treatment strategies that counter ecological disturbances. While our model is relatively abstract and general, it provides some basic insights into the interactions between the relationship between social and ecological processes and how structural properties may come into play. The framework we use to integrate social and ecological process propagating on a social-ecological network can be modified and extended to examine specific questions, or to assess particular empirical patterns observed in specific case studies.

While any number of extensions are possible, we focus on three here that we believe are particularly promising, in part because they move our model towards empirical realism. First, our model does not consider spatial heterogeneity either in disturbance transmission or management efficacy. Yet this type of environmental variation across the landscape is often a natural and important part of real-world systems. Second, our model assumes negative perturbations being transmitted across the ecological network, and management strategies are thus aimed at reducing the overall ecological connectivity. However, in future work this assumption might be relaxed in order to account for beneficial ecological factors flowing across the network, as species migration, pollination, ecosystem flows like water quality and quantity or nutrients. In this latter context, management strategies would aim at increasing the overall ecological connectivity to favor the diffusion of ecological processes (see also Schoon et al., 2014). Third, while we don't vary the costs and benefits of adoption, these are undoubtedly important, in particular with regards to changing the nature of the decision such that it embodies a social dilemma. Because we expect motivations and processes of learning to differ in important ways in the strategic environment of a social dilemma, we expect that we might observe important differences in the relationship between learning and reduction in disturbance prevalence in those environments. These suggestions underscore the fact that our modeling framework can be parameterized in ways that more closely represent specific real-world study systems in order to examine the relationship between structures and processes in those particular systems.

We present this model as an important preliminary step in representing the relationships between learning and decision-making in linked social-ecological systems. While many further complexities await formalization we provide a framework for other modelers interested in representing explicitly the dynamic nature of both the social and ecological systems.

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Ethics statement

No human or animal data were collected for this study.

Data, code and materials

The model protocol is available within the electronic supplementary material. The model code is available at https://www.openabm.org/model/5502/version/1/view.

Conflicts of interest

The authors declare no conflict of interest.

Authors contributions

JB designed and implemented the model. JB designed the analysis and analyzed the results. JB and VH conceived the study, interpreted the results and wrote the paper.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envsoft.2018.08.002.

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