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Title: Effects of multiple behavioral drivers on collective conservation outcomes

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Abstract

Conservation of natural habitats in human-dominated landscapes is critical for halting biodiversity loss. Maintaining habitat quantity and connectivity requires landscape-level collective action, which results from environmental decisions made by individual land owners. We investigate how individual decision making in a rural collective translates into quantitative differences in landscape-level environmental outcomes. Behavioral science has become a critical domain of knowledge in conservation, but little attention has been paid to how multiple behavioral drivers determine the success of collective environmental action. We developed a social-ecological model for landscape-level conservation using a detailed data set of 600 land owners in New Zealand. With the model, we tested whether the effect of social influence networks on collective conservation action was altered by their interplay with land owners' personal characteristics, connections to cross-scale actors and local environmental contexts. Interactions between multiple behavioral drivers determined the environmental outcomes of collective action in unexpected ways by modifying, muting or amplifying the effects of single drivers. Importantly, we detected a social-ecological mechanism for rapid change in the extent of protected habitats, which can explain highly successful or failed environmental outcomes of collective conservation. Further, when environmentally desirable and undesirable behaviors spread simultaneously through the social network, homophily and network cohesion hinder desirable environmental outcomes. This effect can be modified by other drivers such as social responses to local environmental change. Thus, understanding how the antagonistic and synergistic effects of behavioral drivers can be best utilized in conservation will benefit biodiversity and ensure benefits that humans obtain from biodiversity.

Key words: pro-environmental behavior, social-ecological systems, conservation, social networks, landscape structure

Plain-language abstract:
Biodiversity conservation efforts frequently depend on local land owners' participation. However, critical knowledge gaps remain in understanding how individual behaviors collectively lead to desired environmental change. Using an empirically informed social-ecological model for landscape-level conservation, we show that mechanisms emerging from the interplay of behavioral drivers can lead to accelerating environmental change and that effects of single drivers depend on the influences of other drivers. In the context of land owners who vary in their values and relationships, an interplay between behavioral drivers can explain unexpected outcomes of collective conservation, including failure to achieve environmental change. Hence, the benefits of behavioral insights for the success of conservation initiatives depend on better understanding of the ways in which behavioral drivers interact.

Halting global biodiversity loss requires increases in protected areas and efficiency of conservation efforts (1). Protecting native or semi-natural habitat patches on agricultural land can sustain local biodiversity and provide habitat connectivity between existing protected areas (2, 3). Agricultural land covers *circa* 37 per cent of global terrestrial area, and humanity's demand for food, biofuels and fibre is increasing, placing further strain on natural habitats (4–6). Land-use decisions made by individual land owners are thus pivotal in determining the extent of natural habitats and accompanying biodiversity that persist in agricultural land. However, conservation in agricultural landscapes, where the primary objective of individual decision making is often financial, has proven to be a social and ecological challenge (7, 8).

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Conservation is most effective when individuals who have adopted pro-environmental behavior influence broader systems such as social networks and social norms (9–11). Therefore, understanding how the environmental behavior of individuals leads to a system-wide change is crucial for achieving environmental change. A substantial body of literature has considered what motivates individuals to participate in voluntary conservation (12). However, much less is known about why formal or informal collective behavior emerging from individual behaviors in some cases succeeds, and in others fails, in effecting environmental change (10, 13).

Here, we examine how mechanisms emerging from the interplay between multiple constraints and drivers of pro-environmental behavior influence collectively achieved environmental change. The spread of pro-environmental behavior is driven by factors such as social network structure (14) and personal characteristics (15). However, it is likely that multiple ecological and social behavioral drivers *interact* in complex ways to influence environmental outcomes (10, 16), and such interactions cannot be revealed by studies focusing on single drivers (11). To investigate the effects of multiple behavioral drivers, we ask how the effect of social-influence networks on conservation outcomes in agricultural landscapes is modified by cross-scale social influences, actor attributes and local environmental change. We relax the common assumption that influence and behaviors almost inevitably spread between connected individuals (e.g. 14, 17 and references within), and instead assume that: i) behavioral decisions are affected by multiple drivers, and ii) both environmentally desirable and undesirable behaviors[1] can simultaneously spread through a social network (18, 19). Peer influence (i.e. social network connectivity) between land owners can generate desired or undesired environmental behavior and, consequently, patterns of social influence among land owners may determine landscape structure. The propensity of land owners to associate with and be influenced by other like-minded land owners (a process termed 'homophily' [20, 21]) can thus generate socially (but not necessarily spatially) aggregated behaviors. Conversely, social norms and behavior may be transmitted locally ("I see others do it, so it must be a good thing to do") through changes in natural areas, for example among neighboring properties (22, 23). The local influence of social norms on behavior would, therefore, tend to generate spatially aggregated clusters of similar

[1] We use the terms "desirable" and "undesirable" from a biodiversity-conservation perspective. Thus, "environmentally desirable behavior" refers to pro-environmental behavior such as conservation, and "environmentally undesirable" to lack thereof.

behavior(s). The spread of pro-environmental behavior is especially important in natural habitat conservation because biodiversity is strongly influenced by the composition, abundance and spatial configuration of habitats at the landscape level (hereafter, 'landscape structure') (24).

While social structures profoundly impact collective environmental action (see discussion on drivers below), their effects on environmental change are rarely measured (13). We implement a social-ecological agent-based model (Figure 1) to explore how individual decision-making in a rural collective translates into differences in landscape-level native forest conservation. The model is based on survey data of 600 New Zealand land owners that included questions on land use practices, sources of environmental information and personal characteristics (for a summary of the survey methods and general results, see [25]). New Zealand provides an ideal context to explore the emergence of natural habitat conservation on agricultural land: agricultural land covers 42 per cent (in 2015) of the land area (4), and although protecting native habitat on agricultural land is voluntary in New Zealand, the agricultural sector is under societal pressure to improve its environmental performance while maintaining its position as New Zealand's largest sector of tradable goods (26).

Our study includes the following four types (i – iv) of behavioral drivers. First, behavioral science suggests that each person has a set of personal characteristics and beliefs influencing his or her decisions about participation in environmental action (9), which are called (i) *actor attributes* when associated with social networks. Much empirical research has sought to identify the predictors of land owners' adoption of conservation practices (15). A suite of universal predictors has not been identified; instead, they are likely to be context-dependent (15).

Further, behavior, information and ideas spread through (ii) *social networks* as individuals' opinions are weighted in relation to those of others per social influence network theory (27). Threshold models of collective action show that an individual's adoption of a behavior is influenced by the number of people already practicing that behavior and their susceptibility to influence (28). We include network link weights to capture the self-reported level of influence that social connectivity has on each land owner. However, influence-based contagion may actually be driven by homophily (similar people adopt the same kind of ideas), and, over time, actor attributes can become correlated with the structure of social

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networks (29). The importance of the effect of homophily in collective action has been acknowledged, but its effect on collective behavior is not fully understood (21).

The third behavioral driver we consider is (iii) *cross-scale groups,* i.e. social actors who do not directly modify the environment but who may influence other actors to do so, thereby indirectly affecting environmental outcomes (30). Communication between cross-scale actors and local land owners can shift perceptions of conservation and so enhance and coordinate local environmental action (31). Due to their ability to influence environmental chance, we include three cross-scale groups in the experiments and assume them to be pro-environmental. We include two stakeholder groups and one indigenous group but discuss them as one driver.

Finally, humans use the behavior of others to guide their own actions and are generally reluctant to deviate from social norms (32). Consequently, observable cues of widespread support for environmentally desirable action can change behaviors (11, 33). Since both macro-level environmental and social dynamics arise from micro-level social (or social-ecological) interactions (34), local environmental change or reductions in collective behaviors can erode a social norm or affect opinions, ultimately leading to a cascading change in behavior (35, 36). To represent how environmental changes resulting from individual actions feed back to influence future environmental decisions, we include a fourth driver, (iv) *ecological feedback*. Drivers i-iii were derived from the survey results (see Materials and Methods) whereas driver iv was added after the survey was conducted, inspired by the suggestion that when behavior is easily observable, social norms could contribute to widespread change in behavior (37) (see also [38]).

We parameterized the influence of these four types of drivers of environmental behavior on land owners' conservation decisions. We then modeled the spread of environmental behaviors under different parameterizations and evaluated the consequences of land owners' behavior on landscape structure. Four *in silico* experiments were conducted with either two (experiments H_SNA and R_SNA) or all behavioral drivers (experiments H_ALL, R_ALL) affecting land owner decision making (Table 1). The former two experiments include only actor attributes and social network influences as behavioral drivers, and represent a common approach to social network studies explaining environmental outcomes (e.g. 14, 34). The experiments were run with either a survey-based, homophilous network, or using a random

Erdős-Rényi network model (39), which serves as theoretical baseline model to the survey-based networks.

RESULTS

The inclusion of all behavioral drivers in land owner decision making made the environmental outcomes of collective conservation highly unpredictable: a greater range of environmental outcomes emerged for variables measuring protected area extent and fragmentation in experiments with all drivers (H_ALL and R_ALL) than in those with only social networks and actor attributes (H_SNA and R_SNA) (evidenced by vertical spread in Figures 2a-c). Further, the homophilous social networks produces less desirable environmental outcomes (smaller and more fragmented conservation landscapes) than random social networks (Figures 2a-c). In addition, the distribution of the total duration of protection suggests that the random network model regularly produces landscape structure that remains longer under conservation than experiments with homophilous networks (Figure 3, horizontal distribution). However, the constraining effect of homophily was modified when other behavioral drivers were included in experiments. The difference between collective action outcomes of homophily and random social networks is smaller when all driver types were included in experiments (Figures 2a-c, experiment-specific means).

To investigate the mechanisms that underlie the differences in environmental outcomes, we calculated experiment-specific effect sizes (Pearson's *r*) for behavioral drivers and environmental outcome variables (Figure 4). When all behavioral drivers were included in land owner decision making, ecological feedbacks were the strongest mechanism behind collectively achieved environmental change (we interpret effect sizes ≥ 0.5 or ≤ -0.5 as a strong association). In the R_ALL experiment, desirable environmental outcomes of collective action increased with the influence of ecological feedbacks and social networks (we interpret effect sizes ≥ 0.3 or ≤ -0.3 as a moderate association) in decision making. However, when a homophilous network was used, social network influence became muted, and any increase in desired environmental outcomes was driven by ecological feedback alone. This was largely because homophilous networks had a smaller range of network structures than random networks (presented below), and the small structural differences among homophilous networks were insufficient to have a notable impact on environmental outcomes. The desired environmental outcomes of collective action decreased as the influence of cross-scale actors in land owner decision making increased (effect sizes ≤ - 0.3). Actor attributes did not influence environmental outcomes (below effect sizes > -0.3 and < 0.3). However, actor attributes were included in the model both as a separate driver in decision making and through actor attribute-based similarity in the homophilous network construction. Hence, homophilous networks propagate the influence of actor attributes.

Varying the relative influence of the social network and actor attributes, in the experiments where these were the only behavioral drivers (H_SNA and R_SNA), showed that the social network was more effective at generating desired environmental outcomes than were actor attributes when the network was random, but the reverse was true for homophilous networks (Figure 4). To describe the topology of the social network, we measured a number of network indices previously found to be influential in environmental action (Supplementary Information [SI] Table S3). Of the ten network indices we explored, five correlated with the environmental outcomes in R_SNA experiment, and the others not at all (Table 2). This lack of correlation in the homophilous networks was likely due to less variation in network indices for survey-based homophilous networks than for random networks (Table 3, SI Table S4). More generally, the differences in environmental outcomes between homophilous and random network experiments demonstrate that homophily produces less desired environmental incomes by constraining patterns of influence. Survey-based homophilous networks are less compartmentalized than random networks (Table 2, compartmentalization, bridging actors) and have fewer unconnected land owners (i.e. isolates) than random networks, although the number of isolates is high in both (Figure 3, Table 2). Moreover, individual land owners in random networks have more influential links to other land owners (Table 2, average weighted indegree). Consequently, behavioral influences (both desirable and undesirable) can spread widely in homophilous networks, whereas in random networks the spread of influence typically remains within subgroups of land owners. The constraining effect of homophily was larger in experiments including only two drivers, in which the modifying influences of ecological feedbacks and cross-scale social groups were absent.

None of the behavioral drivers correlated with the area of covenanted land in any of the experiments (Figure 4). Since covenanted land cannot legally be unprotected and returned to agricultural use, increase in covenanted areas in our model is mainly influenced by the extent of covenanted areas at the beginning of the model simulations (SI Figure S1).

Finally, comparing environmental outcomes between experiments including all behavioral drivers and experiments including only two behavioral drivers show that only H_ALL and R_ALL experiments produced extreme outcomes in collective conservation, illustrating success or failure in collective action. (Note, our model landscape consists only of areas available for conservation, so the percentages discussed in the study are not directly comparable to suggested critical thresholds in habitat declines that lead to abrupt biodiversity losses, e.g. [41]). For example, the H_ALL and R_ALL experiments produced landscapes in which over 70% of the available land was protected, as well as landscapes in which less than 30% of the land available was protected, whereas the experiments with only social network and actor attribute influences did not produce any such landscapes (Figure 2a). Similarly, we detected greater variance in habitat fragmentation for H_ALL and R_ALL experiments in comparison to H_SNA and R_SNA experiments as well as higher fragmentation (Figures 2b,c), on average. In the case of New Zealand rural land owners, traditional social network analysis approaches would not have been able to address this emergence of extreme outcomes.

DISCUSSION

Taken together, our results demonstrate that interactions between multiple behavioral drivers may determine the environmental outcomes of collective action, including the area and spatial patterning of natural habitat fragments. These interactions occurred in unexpected ways by modifying, muting or amplifying the effects of single drivers. The inclusion of all behavioral drivers in experiments increased the variety of environmental outcomes and led more often to extreme environmental outcomes than our more traditional social network experiment setting, which included only two behavioral drivers. Importantly, the known tendency for people to interact with and influence like-minded individuals (i.e. homophily) generates landscapes with less area and greater fragmentation of natural habitat than would be expected at random. Homophilous social-influence networks reinforce existing behaviors. They thereby produce less successful outcomes, including shorter residence times for protected areas, when both desirable and undesirable behaviors spread simultaneously among heterogeneous actors. Our results suggest that mechanisms emerging from the interplay between multiple behavioral drivers can explain why environmental outcomes of formal or informal collective action range from failure to success.

Extreme environmental outcomes (success or failure of collective conservation) emerged in experiments including all behavioral drivers largely due to a combination of two spread mechanisms, namely spatial diffusion (i.e. ecological feedback) and social connections. While ecological feedback produces spatial clusters of protected or unprotected areas in a landscape, behavior in social networks spreads via social connections, independent of land owners' spatial locations. Behavioral change through social networks can therefore "jump" and produce protected areas in otherwise unprotected regions, or *vice versa*, which then becomes a seed for new ecological feedback-induced clusters (a process similar to long distance dispersal of ecological invasion). This mechanism resulted in a higher level of fragmentation and spatial habitat clustering (i.e. lower entropy) in experiments including all behavioral drivers, especially for homophilous networks, which connect more people. In the context of natural habitat conservation, this social-ecological mechanism generates accelerating gain or loss of natural habitats. In real world systems, inertia effects such as delays in creating or observing local environmental change may slow change.

We found that homophily, a common characteristic of social networks (20), in combination with land owners' self-reported connectivity, typically lowers the success of collective conservation. In our study, the typical cohesive structure of homophilous networks allows both undesirable or desirable behaviors to spread more widely than across the more compartmentalized and fragmented structure of random networks, producing 'compromise' environmental outcomes. Further, because more landowners were connected to at least one other in homophilous networks, this greater proportion had the potential to be influenced by the social network. Finally, similarity among land owners was calculated using actor attributes; land owners who have a high probability of protecting land due to their attributes connected to each other via homophily. In general, this result highlights the importance of considering the influence of actor diversity in collective action. In addition to its influence on the spread of collective action (as studied here), homophily can result in homogeneous ideas within a group, which can further impede the success of collecgtive action when complex problem solving is required (34).

The interplay of behavioral drivers shows, however, that the constraining effect of homophily can be modified. Ecological feedbacks and cross-scale social connections influence land owners who lack network connections to other land owners or who are only connected to like-minded peers. Thus, these drivers can modify the self-reinforcing views that spread through homophilous networks (41). Conversely, social network connectivity only influences land owners that are connected to others. Moreover, the initial extent of covenanted land influenced the final protected area extent since it cannot later be unprotected. Hence, communities that already included committed conservationists were, in our model, better positioned for successful environmental outcomes. A social network with stronger influence links and fewer isolates could, in another setting, outweigh the influence of the ecological feedback.

The influence of social network structures on environmental outcomes has rarely been quantified. That network structure indices correlate with environmental outcomes only when some of the drivers were excluded and that they do so more in random networks than in survey-based homophily networks is challenged by a large body of literature on the significance of social network structures. The outcome we describe results from homophily and context-specific (i.e. survey data) degree distributions, which limit the variability of homophilous network structures that can emerge, despite taking a random sample of land owners at the beginning of each simulation. The effects of social network structures are commonly found to be context-dependent and to interact with other network structures (34). Nevertheless, the differences in environmental outcomes between the homophilous and random models show that network structure strongly influences the outcomes in this study.

Our results have profound implications for understanding the complex milieu of social and ecological processes in which the conservation of natural habitats occurs, especially in human-dominated production landscapes. While drivers of long-term conservation success are social (1, 10, 11, 42, 43), dynamic feedbacks between social and ecological outcomes are rarely considered in conservation science (44) and few studies (e.g. 14) have measured the effect of micro-level social interactions on environmental outcomes. In particular, the two key variables in fragmented landscapes, habitat amount and patterning, can both be determined by the interplay of local environmental feedbacks and social influence. Our approach included a large, detailed dataset, dynamic social-ecological modelling and key drivers for pro-environmental behavior. Hence, we can disentangle a number of potential leverage points for increasing natural or semi-natural habitats on agricultural land. The strong influence of ecological feedbacks suggests that visible sustainable behavior (22) could change the behavior of people who lack social connections (or whose social connections may not promote pro-environmental behavior) and can produce spatial clusters of conservation activity, which would benefit biodiversity. Establishing such "seeds" of conservation could trigger willingness to adopt pro-environmental behavior(s), especially if "seed" land owners commit to long-term conservation via mechanisms such as covenants. A process of land owners encouraging neighbors to undertake private land conservation integrates both ecological feedbacks and social network influence, and this intervention has recently been tested with successful outcomes for landscape-level conservation (38).

Importantly, conservation initiatives based on social network intervention must account for context-dependent network structure and the simultaneous spread of desired and undesired behaviors. Barnes et al. (14), for instance, showed that homophily in a fishery network correlated with unsustainable environmental behavior by limiting the spread of sustainable behavior. Likewise, in our study, homophily in networks resulted in less successful environmental outcomes than random networks. Our results suggest, however, that enhancing communication between homophilous groups to foster the spread of sustainable behavior (14) needs careful consideration as it may also facilitate the spread of unsustainable behavior through the network. Finally, it is crucial to acknowledge that the complex dynamics produced by social-ecological feedbacks may accelerate change: a social-ecological feedback loop including environmental change, emergence of clustered protected areas or strong influence links between spatially decoupled land owners could potentially provide early warning signs for accelerating landscape-level change.

Our model necessarily presents a simplified representation of decision making in social-ecological systems. We assumed that all land owners are able to allocate a fraction of their land to conservation, and we do not consider changes in social or economic conditions or habitat quality. The representation of an ecological feedback is based on the idea that social norms and/or demonstration of conservation action generate a reinforcing feedback. However, a balancing feedback could also result from a decrease in protected areas triggering pro-environmental behavior as land owners observe an increased need for conservation (36, 45). Moreover, the behavioral changes that occur within our model can make the network less homophilous with respect to conservation behavior. Therefore, studies that allow the social network structure to adapt to changing values of landowners during the simulation are needed. Finally, by scaling the total influence of the behavioral drivers to always sum to one we assumed that individual decision making can only be influenced to a certain extent. Hence, an increase in the value of one driver results in a commensurate decrease for the other drivers, which may explain the negative correlation between some drivers and environmental outcomes in the presence of strong drivers. That the weighting of stronger drivers (e.g. ecological feedback) may decrease as the influence of cross-scale groups (which each had their own weighting) increases may explain the negative effect of these cross-scale groups. However, it is more likely that the weak influence was due to the low number of land owners connected to cross-scale actors: in our sample of 600 land owners, only 1.8% of land owners reported influential environmental conversations with indigenous groups, 28.3% with local councils and 3.0% with central government representatives. In that case, conservation initiatives using cross-scale groups as influencers would not have produced desired environmental outcomes in our study context.

In conclusion, our work emphasizes that an interplay between behavioral drivers can produce unexpected environmental outcomes in collective conservation action. Long-term protection of natural and semi-natural habitats in human-dominated landscapes necessitates understanding that the drivers influencing environmental behavior are not necessarily additive but may include antagonistic and synergistic effects. Understanding how these effects can be best used in conservation design will benefit biodiversity and ensure the benefits that humans obtain from biodiversity.

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AUTHOR CONTRIBUTIONS

JY and JT conceived the study idea, and the study was designed by all authors. PB designed and enumerated the survey. JY and GP built the Land User Model with input from JT. JY performed the analyses with input from JT and GP. JY and JT interpreted the results. JY wrote the initial manuscript and all authors contributed to writing the final version of the manuscript. JT, PB, GP and RP secured funding.

MATERIALS AND METHODS

General model concept

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We developed an agent-based model for evaluating the environmental outcomes of collective conservation action on agricultural land (Figure 1). A detailed Overview, Design concepts and Details (ODD) protocol of the model is available in the SI. Data for the study were collected in the 2015 Survey of Rural Decision Makers (46), which is a large, internet-based survey covering 3300+ farmers in all primary industries and all regions of New Zealand. Due to question randomisation and the survey branching, the usable data set for this survey included 600 commercial land owners.

Model simulations begin with 200 land owners, randomly selected for each simulation from the 600 land owners with complete survey data. At the start of each simulation, protected natural habitat is present only on the farms of the land owners who reported having native forest or covenanted land. At each time step, land owners decide whether to protect natural habitat on their land, and if they decide to protect the land, they also decide whether to covenant[2] it. In the model, self-reported barriers such as fear of losing rights to own land prevented land owners from committing land to covenants. Land owners can decide to not protect land only if the habitat is not covenanted. During the following time step, decisions take place in an updated social-ecological context. We simulated a period of 150 time steps, which represents approximately 15 years. The model was run for 50 time steps burn-in before analysis.

The landscape component of the model is represented on a toroidally wrapped grid (lattice). Each cell in the landscape can occupy one of three states: protected, unprotected, or covenanted. For habitat connectivity variables, connected protected cells are assumed to create a non-fragmented habitat area; any non-protected cells between protected patches indicates the presence of habitat edges. The landscape consists only of land available for conservation (i.e. no other land use), and is subdivided into farms owned by the 200 land owners represented in the simulation. We allowed 10% of each farmer's land to be available for protection and assumed that the farm would remain financially viable. This simplification avoided the possibility of unlikely outcomes such as land owners protecting 100% of their land while allowing us to avoid further complicating the model by including financial parameters. We assumed that the extent to which individuals prioritise profit over

[2] Covenanting land is a practice increasingly adopted by land owners in New Zealand. It is an agreement between a private land owner and the QE II National Trust to protect land, even if the property is sold to a new owner (54).

conservation are captured by the actor attributes, which were measured in the survey. This percentage was arbitrary but was held constant across experimental treatments. The size of each farm is based on survey data.

To determine a set of actor attributes that influence native forest protection, we performed logistic regression analyses on variables covering land owners' views and values for conservation and covenants, their farming industry, land use and whether they live on the farm (SI Tables 5a-d, a detailed examination of the diversity of survey land owners can be found in [26]). The entire set of 28 variables (SI Table S7) included in the regression was used to calculate pairwise Gower's dissimilarity (47) for the 600 land owners. The probability of each pair of land owners (with indegree > 0) to be connected was inversely proportional to their dissimilarity in their attributes, thereby generating homophilous connectivity.

In social networks, nodes represent land owners and directed links represent influential environmental conversations between peers. Each land-user's indegree and link weight were reported in the survey respectively as the number of other land owners which whom they had environmental conversations and a categorical evaluation (four categories) of the influence of these conversations (SI: Network Questions). We removed links in which the level of influence was reported as "not influential". Because the survey captured the number and level of influence but not the identity of influence partners, connectivity between individuals was assigned either at random or homophilously at the start of each simulation. Random networks follow the Erdős–Rényi models (39); we used the mean link density of > 6500 model-generated homophily networks (0.0035) as the probability of assigning a link between any two land owners. Three categorical link weights representing slight/moderate/high influence were assigned at random. These random network models are a null against which to compare the influence of homophily. We included a set of cross-scale groups, specifically central government representatives, local council representatives and an indigenous group (New Zealand Māori iwi). Links to cross-scale groups and their influence were reported similarly by land owners. In both network structures, the number of nodes (land owners to create links between) was fixed at 200.

Simulations

The influence of each behavioral driver on decision making was scaled to sum to one (Table 1). We varied the percentage of land owners who make a decision during each time step (30, 70 or 100%) as well as the minimum time interval between land use changes (0, 2 or 6) for each parameter combination. One simulation was run for each parameter value combination for the experiments, including all behavioral drivers, resulting in 6561 simulations per experiment. H_SNA and R_SNA experiments (with fewer unique combinations due to fewer drivers) were run with repeated simulations (n = 75) to total to 6561 to have a consistent number of simulations for each experiment.

Land user decision making

Decision making was calculated as the weighted sum of the behavioral drivers. Each behavioral driver had a value between 0 and 1, with higher values indicating a higher likelihood of protecting land. Network influence indicates the number and influence (weight) of links that a land owner has to other land owners that are protecting land across all the actor's weighted links. It is based on weighted indegree centrality and was calculated for actor i as:

$$C_d(i) = \frac{\sum_{j=1}^{nc} x_{ij} w_{ij}}{\sum_{j=1}^{n} x_{ij}\, w_{ij}} \tag{1}$$

where n is the number of nodes in the network, nc is number of nodes currently conserving habitat on their land, x is the value of the link (1 if the nodes are connected) and w is the link weight.

The network influence for each cross-scale actor group was calculated in relation to the maximum cross-scale influence (C_{max}) in the network:

$$C_{cs}(i) = \frac{k w_c}{C_{max}} \tag{2}$$

where k is the land-user's degree to that cross-scale group and w_c is the influence of those links (both derived from survey data). The ecological feedback for actor i was calculated as:

$$E(i) = \frac{N_c}{N} \tag{3}$$

where N_c is the count of adjacent farms with native forest and N is the total number of adjacent farms.

Actor attribute influence was calculated from a logistic regression with the protection probability of native forest (outcome variable) and survey responses as predictors (X), calculated as:

$$P(Y) = \frac{1}{1 + e^{(b_0 + b_{1i}X_{1i} + b_2 X_{2i} + \dots b_n X_n)}} \qquad (4)$$

where b_n is the regression coefficient for variable X_n.

The probability of land being covenanted was calculated similarly, but with the exception that if the actor had reported (in their survey responses) reasons for not covenanting land (e.g., no suitable land available on farm or concerns over covenant regulations or losing the right to change covenanted land), they would always decide against it.

Finally, in our representation of decision making, the influence of each driver is weighted by his or her individual parameter values. The probability of an actor protecting land is the weighted sum of n behavioral drivers:

$$P(protect) = \sum_{j=1}^{n} y_j f_{ij} \qquad (5)$$

where y_j denotes the weight (parameter value in our model) of importance of each behavioral driver in decision-making, and f_j is the value of the behavioral driver.

Data and software availability

We used NetLogo 6.0.3. (48) for model programming and simulations, including the R extension (49), and R Studio version 1.1.463 coding environment for supporting coding and analysis (50). Pseudocode for the model and needed data input files for the model are available in SI. Sample data for actor attributes is available in https://www.dropbox.com/s/l99ockib7c3rvvo/Yletyinen_sample_data_LU1_2019.xlsx?dl=0 (*a temporary link for the journal review, to be replaced with data repository link*) and the full data-set can be requested from the authors with consideration to survey respondents' anonymity. Simulated, simplified landscapes and subsamples of land owners make the survey respondents unidentifiable in the model.

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FIGURE AND TABLE CAPTIONS

Figure 1. General model concept. The model consists of A) three cross-scale actor groups and their influence links to land users; B) 200 heterogeneous land owners, each with his or her personal attributes, and influence links between land owners; C) a simulated agricultural landscape with areas available for conservation on each farm, upon which the land owner makes conservation decisions (dashed line); D) a binary ecological landscape emerging from conservation action and consisting of either protected or unprotected land, coloured here accordingly; E) ecological feedback to each land owner from his or her neighbouring farms (here illustrated with one arrow only). A-B link weights represent the level of influence that land users have self-reported their connections to have.

Figure 2. **The main environmental outcomes.** Comparison for experiment-specific outcomes are shown as bean plots (horizontal black lines represent averages for experiment-specific distribution and dashed lines represent overall averages). The length of the bean per

point found is 0.1. The high ends of the beans are cut to a maximum value of 0.2 for visibility of the distribution. The variability of outcomes across simulations was also greater when all behavioral drivers were included, and the mean level of environmental outcomes was lower with a homophilous network. The models are abbreviated as H_ALL: homophilous network model influenced by all drivers (actor attributes, social network, ecological feedback and cross-scale actors); R_ALL: random network model influenced by all four factors; H_SNA: homophilous network model influenced by social networks and landowner attributes only; and R_SNA: random network model influenced by social networks and actor attributes only. The figure was produced using the beanplot R package (50, 51)

Figure 3. The average temporal variation in the size of protected area during model simulation. The distribution of residence time (the total duration of land as protected) for the homophily model with all behavioral drivers shows the shortest average duration for protected areas and no extreme outcomes. The random model excluding external variables produces the most long-term protected areas. The number of isolates plays a role as the fraction of the rural collective that cannot be reached through social networks and was found to be higher in random networks than in survey-based homophilous networks. The figure was produced using the ggpubr R package (50, 52).

Figure 4. Scenario- and model-specific effect sizes. Behavioral drivers included in decision making by land owners are marked with a black rectangle, and the remaining variables on the y-axis are social network indices. The figure was produced using the gplots R package (50, 53).

Table 1. Model experiments. In each experiment, the effect of behavioral drivers was tested by systematically changing their influence in decision making. Cross-scale groups include indigenous group (New Zealand Māori iwi), local council representatives and central government representatives. ‘Change-makers’ is the percentage of land owners making a decision during each time step, and ‘time steps’ is the minimum time interval between land use changes. Neither of these is a behavioral driver.

Table 2. Social network indices. Calculated from networks for both two-factor and four-factor experiments, a total 13 122 simulations (6561 each). Density was used in network

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randomization in R_SNA and R_ALL experiments. The full table and descriptions for each social network analysis index can be found in SI tables S3 and S4.

FIGURES

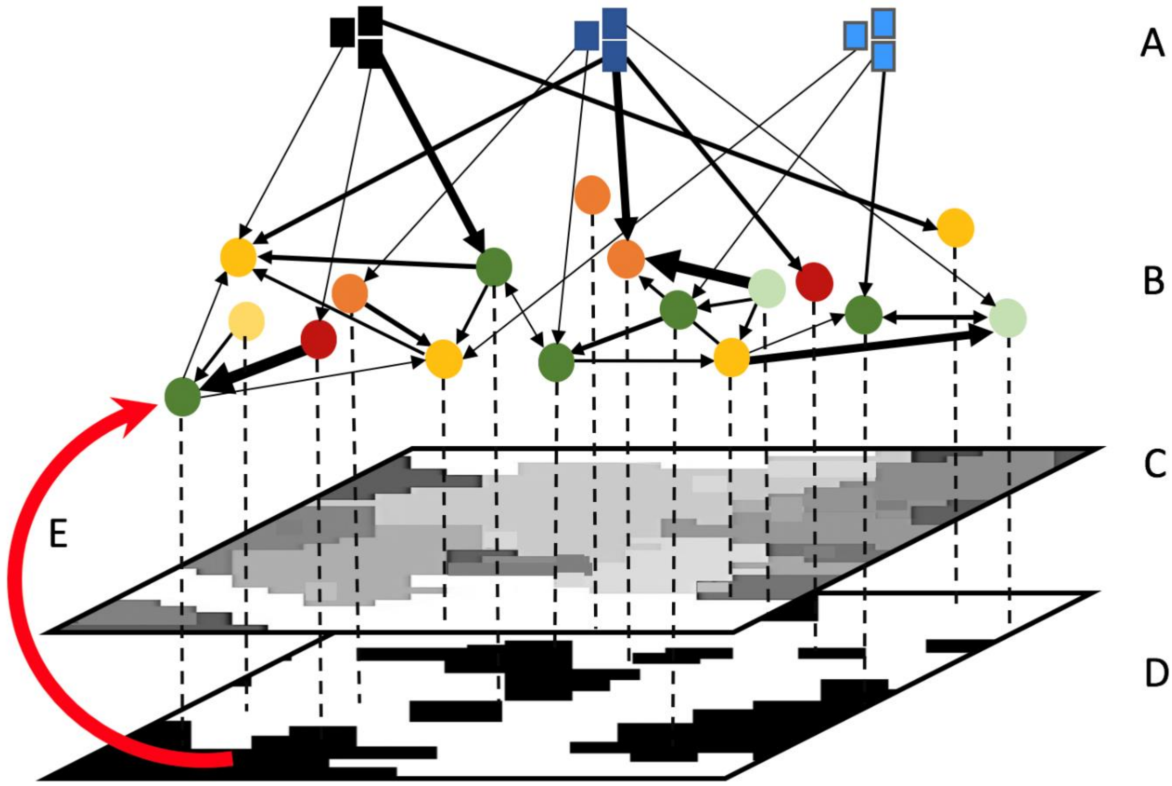
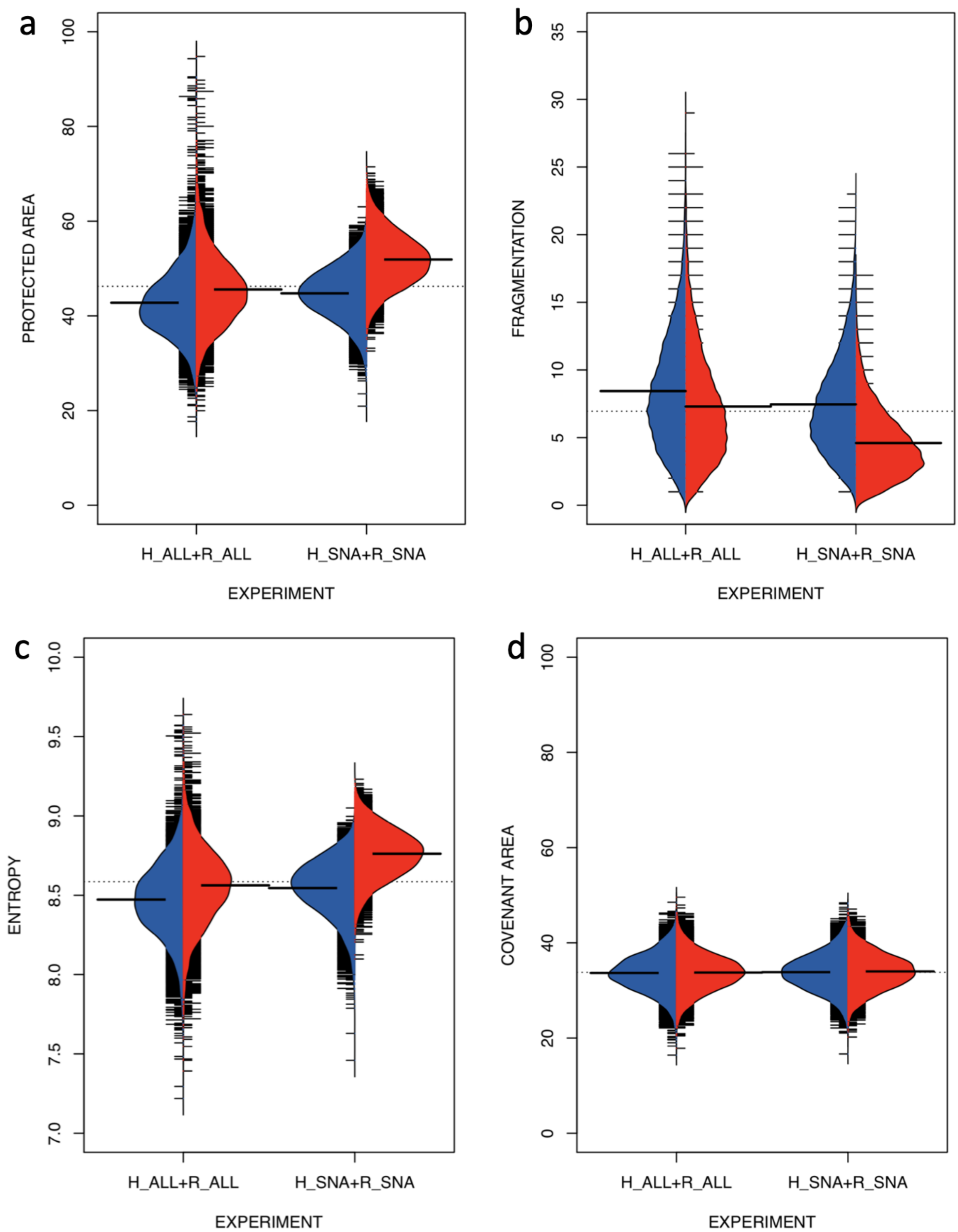


Figure 1.


a
b
c
d
PROTECTED AREA
FRAGMENTATION
ENTROPY
COVENANT AREA
H_ALL+R_ALL
H_SNA+R_SNA
EXPERIMENT

Figures 2a-d.

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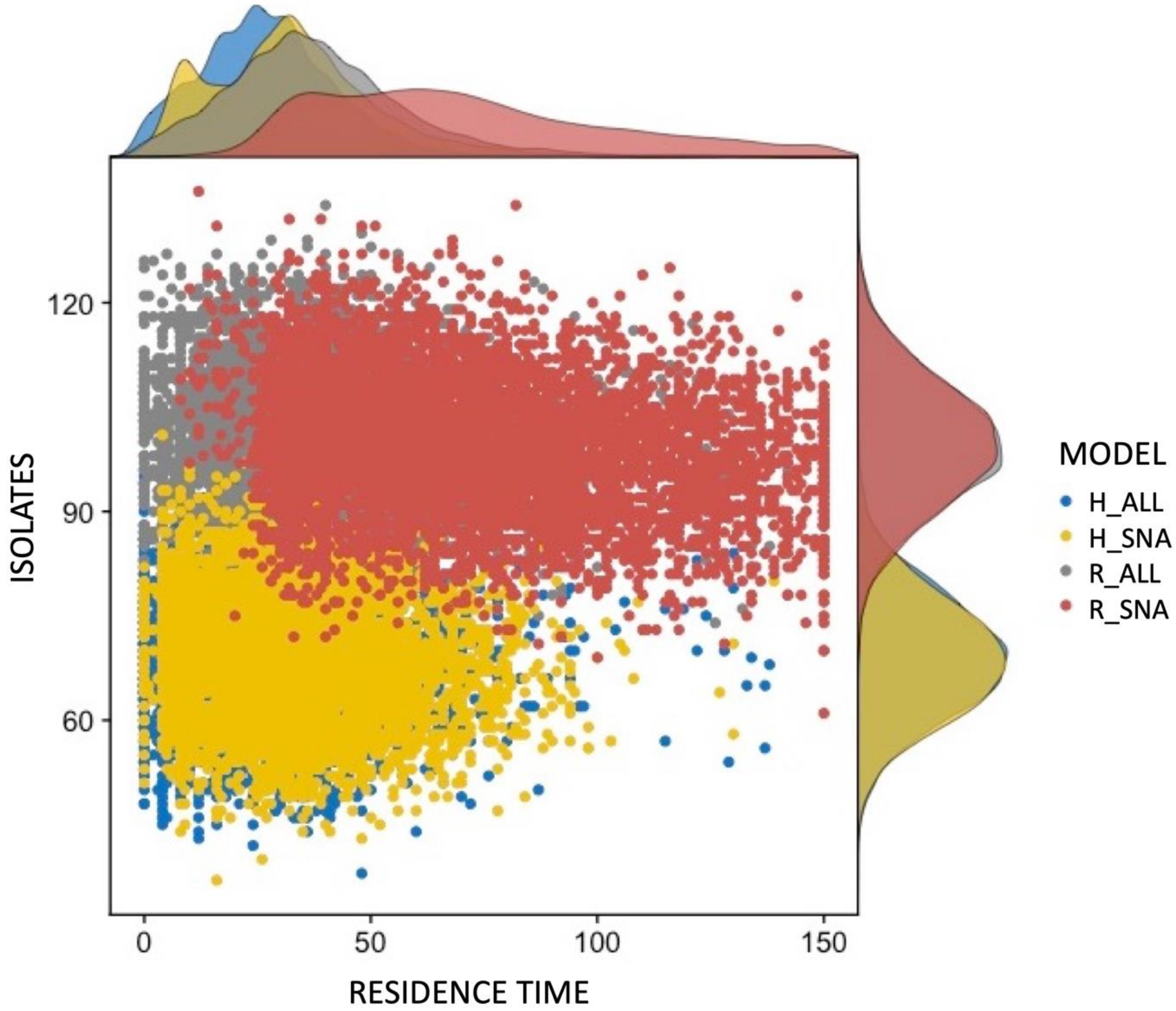

Figure 3.

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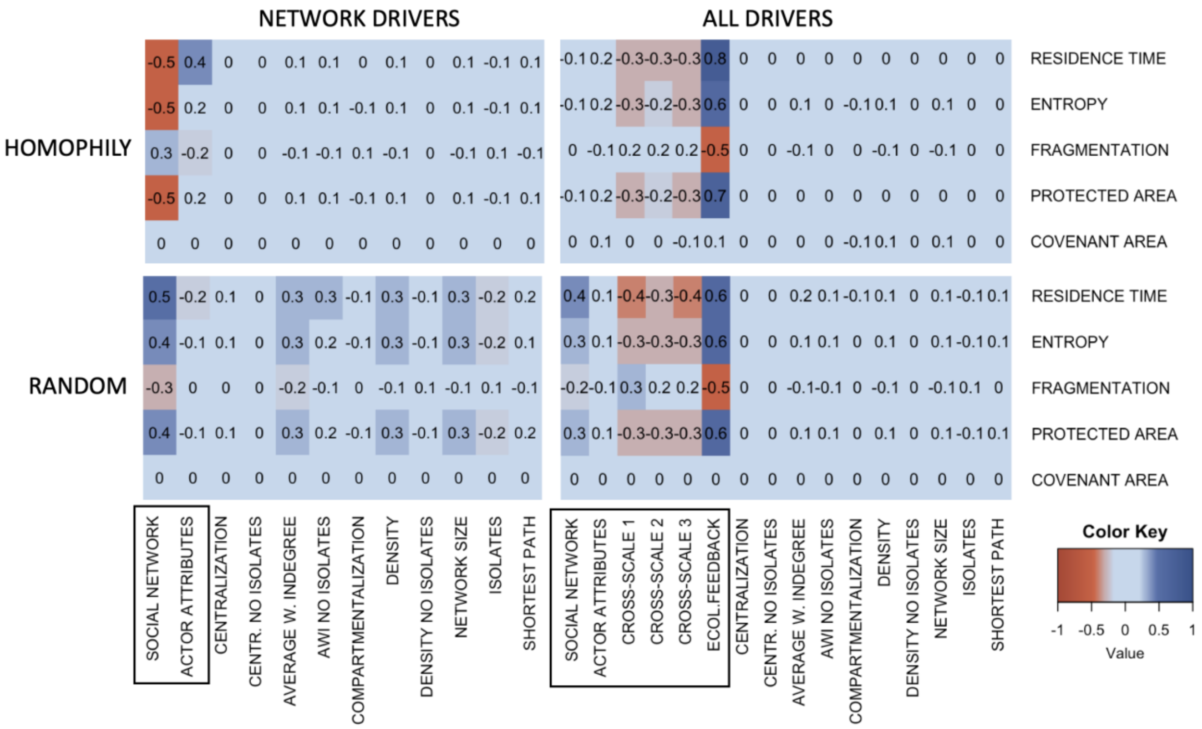

Figure 4.

TABLES

Table 1.

EXPERIMENT AND BEHAVIORAL FACTOR TYPES	NETWORK MODEL	PARAMETER VALUES
H_ALL i) Actor attributes ii) Social network iii) Cross-scale groups iv) Ecological feedback	Homophily	Actor attributes: 0.1, 0.5, 1 Social network: 0, 0.5, 1 Cross-scale groups - Indigenous: 0, 0.5, 1 - Council: 0, 0.5, 1 - Central gov.: 0, 0.5, 1 Ecological feedback: 0, 0.5, 1 Change-makers: 0.3, 0.7, 1 Time steps: 0, 2, 6
R_ALL i) Actor attributes ii) Social network iii) Cross-scale groups iv) Ecological feedback	Random	Actor attributes: 0.1, 0.5, 1 Social network: 0, 0.5, 1 Cross-scale groups - Indigenous: 0, 0.5, 1 - Council: 0, 0.5, 1 - Central gov.: 0, 0.5, 1 Ecological feedback: 0, 0.5, 1 Change-makers: 0.3, 0.7, 1

		Time steps:	0, 2, 6
H_SNA i) Actor attributes ii) Social network	Homophily	Actor attributes: Social network: Change-makers: Time steps:	0.1, 0.5, 1 0, 0.5, 1 0.3, 0.7., 1 0, 2, 6
R_SNA i) Actor attributes ii) Social network	Random	Actor attributes: Social network: Change-makers: Time steps:	0.1, 0.5, 1 0, 0.5, 1 0.3, 0.7, 1 0, 2, 6

Table 2.

SOCIAL NETWORK INDEX	HOMOPHILY NETWORK	RANDOM NETWORK
Network size	91.000 **142.726** 217.000	74.000 **139.117** 212.000
Bridging actors	26 **46.272** 70.000	8.000 **30.565** 60.000
Isolates	37.000 **69.262** 101.000	61.000 **99.657** 136.000
Compartmentalization	0.210 **0.677** 0.911	0.791 **0.934** 0.974
Average weighted indegree without isolates	0.523 **0.723** 0.979	0.642 **0.918** 1.225
Density	0.002 **0.004** 0.005	0.002 **0.003** 0.005
Density without isolates	0.006 **0.008** 0.012	0.010 **0.014** 0.021

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Supplementary Information for:

Effects of multiple behavioral drivers on collective conservation outcomes

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This PDF file includes:

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Supplementary Information Text:

Network questions in the Rural Decision-Makers 2015 Survey

This section describes how the *Rural Decision-Makers 2015* survey data (1) were converted to a social network structure. In the social network including only land owners, each node is an individual land owner, and each link represents influence mediated by conversations about environmental issues. First, land owners were asked "*Did you regularly meet with individual people from the following groups to discuss environmental performance of your farm business over the past 12 months*?" If a land owner chose "*Farmers in your industry" or "Farmers in different industries"*, they received two additional questions on the number and influence of connections they have to other land owners. The in-degree (number of incoming links) is based on the land owners reply to the question: *"With approximately how many individuals from each of the following groups did the trust board regularly meet to discuss environmental performance of the farm business during the past 12 months?".* Then, the land owners evaluated the influence (*"How influential is advice about environmental performance from these individuals?")* on four-categorical scale: not at all influential, slightly influential, moderately influential, extremely influential. The answers were quantified and standardized to numeric link weights (0, 0.33, 0.66, 1). If a land owner replied "*Not at all influential"*, the link weight becomes zero and the land owner's in-links to other land owners are removed from the network.

The second level of the network, i.e., land owners' links to stakeholders, include survey-based data on the indegree (i.e. connectivity between a land owner and representatives of New Zealand Māori iwi). The land owners were also able to select stakeholder groups in the question "*Did you regularly meet with individual people from the following groups to discuss environmental performance of your farm business over the past 12 months*?") and influence (*"How influential is advice about environmental performance from these individuals?").* We did not include stakeholders as nodes in the model networks since it would have required inventing the total number of cross-scale actors available (the model does not represent any specific area) and we do not know whether the land owners have talked to the same or different individuals in stakeholder groups. Thus, we avoided making assumptions about the topology of intermediate social network linking the land owner and stakeholder levels. Instead, cross-scale actor data is stored as land owner variables.

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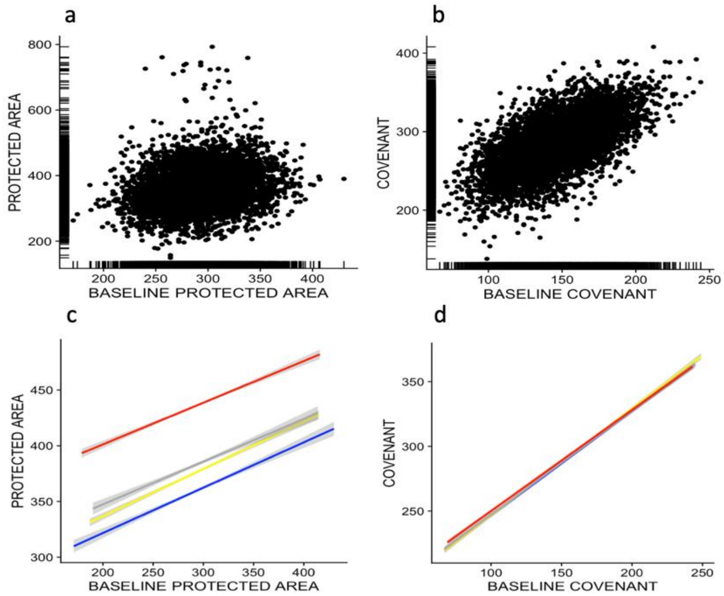

Fig.S1a-d. Relationship between baseline habitat and environmental outcomes. Due to diffusion processes (ecological feedback, social network influence), the extent of protected area in the beginning of model simulation affects the extent of protected area and covenanted area in the end of model simulation. (a) shows the relationship between the extent of protected area in the beginning (baseline) and at the end of model simulations, for the experiment including a homophilous network and all four behavioural factors. The x- and y-axis units represent number of protected grid cells on the landscape model (total 841 cells). (b) shows the same relationship for covenants, suggesting that the relationship is more linear because covenanted land cannot be unprotected. Note that in figure a, the most successful protection cases occur with circa 250 – 350 baseline habitat area, not the highest. Figures c and d shows the same trends as regression lines to illustrate experiment-specific differences, with confidence interval 0.95. The blue and gray lines represent homophily (H_ALL) and random (R_ALL) network experiments with all four factors included, respectively. Yellow and red lines represent homophily (H_SNA) and random (H_SNA) network experiments, respectively, including only social network influence and actor attributes. Contrary to protected area, experiment-specific differences in the resulting extent of protected area were not detected for the increase in covenanted areas.

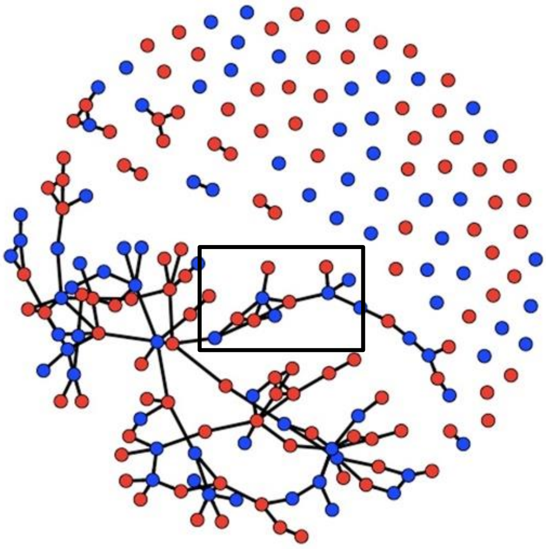

Fig. S2. A homophilous network of land owners, as captured from one of the homophily scenario one simulations. Blue nodes represent land owners who have protected natural habitat on their land, red nodes are land owners without protected land. Note the mix of blue and red land owners on structures where network influence alone would have produced only unicolor nodes; for instance, see area marked with a black box. The isolates (unconnected nodes) represent land owners who reported they either did not frequently talk to other land owners about environment, or that such discussions were not influential to them. Isolates may emerge in survey data collection (e.g., 2) and are included in the network as they may play an important role in environmental or resource collectives. The network was visualized using the Fruchterman-Reingold layout (3, 4).

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Table S1. Survey-based actor attributes and additional landscape variables included in the model. Prefix 's' in front of the ID number indicates Rural Decision-Makers survey-based variables, whereas variables calculated in the model can be found in Table S2 (prefix 'm'). In the Variable column, a letter indicates the reply options for each survey question: (B) binary (yes/no) reply, (C) categorical reply, (N) a value reported by the land owner. We assume any additional variables to be constant across the land owners throughout the modelled time period. These variables may include economic (e.g., market forces), political (e.g., policies that increase the productivity of the land and make setting aside land for conservation a greater loss) and institutional factors (e.g., attitudes on the public having right to recreational natural spaces).

ID	VARIABLE	DESCRIPTION
Land use and natural environment on the farm		
s1	Land use (C)	Land use on the farm. Selecting multiple options was allowed in the survey; in the model, each land use is a variable of its own. Land use options: - grazing livestock - operating a dairy platform - operating a dairy run off - farming sheep and or beef - raising and/or finishing prime cattle, including bull beef - raising deer - raising pigs - raising poultry birds - raising other farmer livestock - growing grain and seed crops - growing crops for hay, silage or balage - growing vegetables and/or cooking herbs indoors - growing vegetables and/or cooking herbs outdoors - growing flowers, bulbs, nursery crops, or hops - growing kiwifruit - growing wine grapes - growing other fruits, nuts, or edible tree crops - plantations of exotic trees inteded for harvest - harvested exotic forest area awaiting restocking - farm-based tourism - wetlands **- native forest and shrubs and/or tussock grasslands: farm land contains native forest and shrubs and/or ungrazed tussock grassland. This variable was used as an indicator of protected land on a farm, and as an outcome variable in regression analyses.**
s2	Covenant (B)	All or part of the land is covenanted, i.e., permanently protected.
Farming characteristics		
s3	Primary industry (C)	Land owner's primary activity, i.e., how the land owner primarily identifies him/herself as a farmer. Selecting multiple options was allowed in the survey. Primary activity options: - farming sheep - farming beef - farming sheep and beef - dairying - deer farming - grazing livestock not owned by the farming business - pig farming - poultry farming - other farmed livestock - arable farming

		- vegetable production - growing flowers, bulbs, nursery crops, or hops - kiwifruit production - wine grape production - growing fruits, nuts, or edible tree crops - exotic forestry - farm-based tourism - native forest and shrubs and/or tussock grassland - other
s4	Ownership (C)	Ownership of the land: myself (land owner) / another individual / family partnership / family trust / family company / Māori trust or inc. / corporate owned / equity partnership / family company
s5	Live on farm (C)	The land owner lives on the farm: year-round / part of the year / not at all.
s6	Area (N)	The total area of the farm in hectares. This variable addresses the largest land parcel of the farm, even if the farm includes additional blocks.
Personal values		
s7	Private conservation (C)	Private land owners should protect habitat for native plants and animals on private land: strongly disagree / middle / strongly agree.
s8	Public conservation (C)	The New Zealand Department of Conservation should protect habitat for native plants and animals on public land: strongly disagree / middle / strongly agree.
s9	Covenant barriers (C)	The reasons why land owner has not joined a covenant: don't have suitable land / fear of losing property rights / too much regulations. In the model, each reason is a variable of its own.
Social networks		
s10	Indegree (C, N)	The number of connections a land owner has to other land owners and to each cross-scale actor group. This variable consists of two parts: i) whether the land owner has regularly met to discuss environmental performance of the farm with representatives from the following actor groups (C); and ii) with approximately how many representatives of each group they have met regularly (N). Indegree for any of the stakeholder subgroups can be zero if a land owner has no connections to that group. The model includes following network actors: - regional councils, district councils - central government - iwi, i.e. largest social units of māori in New Zealand, often translated to “tribe” in English. In this study, we call iwi “indigenous groups”. - farmers in the same industry as land owner - farmers in different industries than land owner
s11	Social influence (C)	Land owner's estimation of how much influence his/her social connections (see list on the stakeholder subgroups in variable s10) have on him/her: not at all influential / slightly influential / moderately influential / extremely influential. If the connection is "not at all influential", land owner's degree to that actor group becomes zero in the model.

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Table S2. State variables included in the study.

Variable	Description
Baseline protected area	The extent (number of patches) of protected area in the beginning of simulation
Baseline covenant	The extent (number of patches) of covenanted area in the beginning of simulation
Protected area	The extent (number of patches) of the total protected area in the landscape, measured at the end of simulation
Covenant area	The extent (number of patches) of the total covenanted area in the landscape, measured in end of simulation
Fragment count	The number of natural habitats fragments (a fragment is defined as a protected area surrounded by land in other use) at the end of simulation
Entropy	A measure (Shannon entropy, (5)) of spatial randomness / arrangement of the natural habitat fragments in landscape, measured at the end of simulation
Residence time	The total length of time (number of time steps) that land was protected, even if discontinuous. The average protection time was calculated from a list of protection times for each patch, and it excludes 50 first steps for model initiation.
Conservationists	The number of land owners who have protected native forest, calculated in the end of simulation
See Supplementary Materials Tables S3 and S4 for social network analysis indices.	

Table S3. Structural social network indices. The indicators included in the study were chosen based on influence on collective action or environmental management described in previous studies. Due to the high number of isolates in our networks, some indices were calculated with and without isolates.

SOCIAL NETWORK INDICES	
INDEX	RELEVANCE
Mean path length: the average of shortest paths between all actor (node) pairs (6)	A short mean path indicates that everyone in a network is fairly 'close' to each other, and actors can thus reach each other through a small number of intermediate actors (cohesive network) (6).
Density: the ratio between the actual number of links in a network and the number of possible links (6)	Density affects collective action as increased possibilities for communication (influence), exposure to new ideas and knowledge (7). However, very high density may hinder efficiency of collective action, or lead to homogenization (7). In influence network, short mean path and density would thus lead to quick spread of attitudes, knowledge and behaviour.
Centrality: how central the network's most central actor is in relation to how central all the other actors are (8)	While density and mean path describe the overall cohesion of a network, centralization describes the extent to which this cohesion is organized around particular actor(s) (7). High degree of centralization may have a positive effect on collective action as a central actor can prioritize certain action, and even coordinate the action, but it also indicates asymmetric influence relations (7). Hence, a highly centralized network would indicate a presence of central actors who are in key position to influence a large proportion of the land owner collective.
Compartmentalization: a presence of subgroups in which actors are joined together in tightly connected groups, between which there are fewer connections (9)	The low density of links between compartments may have negative effects on the collective action (see Density), and may lead to "them and us" attitudes, but high density inside compartments may lead to developing specialized knowledge (7). In the case of homophilic influence network, compartmentalization indicates subgroups of like-minded people with fewer connections (that would allow spread of attitudes and behaviour) to people less similar to them.
Bridging links: links connecting different actor subgroups. Here, we measure bridging links as number of cut points (articulation points): actors whose removal increases the number of connected components in a network by forming two or more separate subgroups between which there are no connections (6).	By connecting network subgroups (potentially compartments), bridging links provide actors in subgroups access to external knowledge and resources. Thus, high number of bridges enable or support collective action among different groups of actors. In this study, we calculated number of cut-points (i.e. actors who connect subgroups/network components. Removal of cut-point actors leads to a network subgroup breaking into two with no communication in between) to indicate number of bridgers.
Isolates: non-connected actors	Actors who do not participate in local network because they do not have links to other actors (based on the network boundary setting). In our study, actors who had not had frequent, influential discussion about environmental performance of the farm. Our 'Isolates' network index shows number of isolates.
Average weighted degree: the average number of connections that actors in a network have, including the link weights.	Actor's network degree is the number of immediate contacts that an actor has in a network, enabling access to knowledge, new ideas, resources, etc. In our study, link weight indicates influence. Thus, high average weighted degree would mean a network with strong peer influence among the actors.

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Table S4. Structural social network indicators for homophily and random networks. The bold value is the mean (for which standard error (SD) is calculated), value above it the minimum value, and below it the maximum value for all simulations. Due to the high number of isolates in our networks, we have calculated some indices with and without isolates. Network size is the number of links in the network. Erdős–Rényi randomization was based on the average density of homophily networks, and should thus be similar for homophily and random networks.

SOCIAL NETWORK INDEX	HOMOPHILY NETWORK	HOMOPHILY SD	RANDOM NETWORK	RANDOM SD
Mean path length	1.224 **2.210** 6.232	0.569	1.211 **2.528** 8.496	0.808
Network size	91.000 **142.726** 217.000	16.154	74.000 **139.117** 212.000	16.760
Number of cut points	26 **46.272** 70.000	6.175	8.000 **30.565** 60.000	6.522
Centralization	0.007 **0.015** 0.030	0.003	0.006 **0.016** 0.032	0.004
Centralization without isolates	0.008 **0.021** 0.050	0.005	0.006 **0.025** 0.067	0.007
Average weighted indegree	0.289 **0.473** 0.729	0.057	0.205 **0.461** 0.704	0.060
Average weighted indegree without isolates	0.523 **0.723** 0.979	0.060	0.642 **0.918** 1.225	0.068
Compartmentalization	0.210 **0.677** 0.911	0.095	0.791 **0.934** 0.974	0.019
Density	0.002 **0.004** 0.005	0.000	0.002 **0.003** 0.005	0.000
Density without isolates	0.006 **0.008** 0.012	0.001	0.010 **0.014** 0.021	0.001
Isolates	37.000 **69.262** 101.000	8.689	61.000 **99.657** 136.000	9.241

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Tables S5a-d. Stepwise logistic regression analyses with forward selection were used to examine which variables could influence land owner's probability to protect native habitat for biodiversity, and thus, be used as actor attributes. Tables S5a shows maximal models with variable "*farm land contains native forest and shrubs and/or ungrazed tussock grassland*" (Table S1 variable s1), and Table S5c maximal model with variable *"All or part of the land is covenanted"* (Table S1 variable s2) as dependent variables. S5b and S5c present the results, respectively. The results include only land use variables. This is partly because both our dependent variables were essentially describing land use. Further, it is likely that land owners' values, ownership and choices required by the primary industry are already reflected in land use. Collinearity was detected only for land use variables. Significance codes for p-values: ***: < 0.001, ** < 0.01, * < 0.05, . < 0.1.

Table S5a.

ID	Variable	Estimate	Std. Error	z value	Pr(>|z|)	
	(Intercept)	-1.95E+00	2.11E+00	-0.926	0.354311	
s7	Private land owners should protect habitat for native plants and animals on private land: 7	-5.31E-01	4.27E-01	-1.241	0.214547	
s7	Private land owners should protect habitat for native plants and animals on private land: 8	-4.21E-01	4.23E-01	-0.996	0.31948	
s7	Private land owners should protect habitat for native plants and animals on private land: 9	-7.86E-01	4.75E-01	-1.655	0.097961	.
s7	Private land owners should protect habitat for native plants and animals on private land: 10	-9.22E-01	4.80E-01	-1.92	0.054872	.
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 1	-1.51E+01	3.96E+03	-0.004	0.996959	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 2	-1.52E+01	1.94E+03	-0.008	0.993766	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 3	-2.95E+01	1.95E+03	-0.015	0.987893	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 4	-5.26E-01	2.37E+00	-0.222	0.82414	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 5	3.57E-01	2.11E+00	0.169	0.866028	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 6	-9.83E-01	2.07E+00	-0.476	0.634054	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 7	-1.38E-01	2.04E+00	-0.068	0.945994	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 8	-4.89E-01	2.03E+00	-0.241	0.809854	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 9	5.75E-02	2.04E+00	0.028	0.977491	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 10	3.62E-01	2.03E+00	0.179	0.85801	
s2	Has covenant on own land	1.22E+00	3.30E-01	3.694	0.000221	***

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s4	Land ownership: myself	-1.35E+00	1.14E+00	-1.176	0.239723	
s4	Land ownership: another individual	-2.04E-01	4.18E-01	-0.487	0.626112	
s4	Land ownership: family partnership	-1.66E-01	4.33E-01	-0.384	0.701343	
s4	Land ownership: family trust	2.64E+00	1.68E+00	1.568	0.116814	
s4	Land ownership: family company	-1.71E+01	1.14E+03	-0.015	0.988042	
s4	Land ownership: māori trust / inc.	3.98E-01	6.45E-01	0.618	0.536722	
s4	Land ownership: corporate owned	6.35E-01	4.70E-01	1.35	0.177038	
s6	Area	8.61E-05	1.31E-04	0.658	0.510582	
s3	Primary industry: grazing livestock, not own	-9.33E-01	6.90E-01	-1.353	0.175908	
s3	Primary industry: farming sheep	-4.61E-01	6.57E-01	-0.701	0.483603	
s3	Primary industry: farming beef	-5.64E-01	6.57E-01	-0.857	0.391223	
s3	Primary industry: dairying	5.22E-01	1.25E+00	0.418	0.675597	
s3	Primary industry: deer farming	1.06E-01	1.12E+00	0.095	0.924602	
s3	Primary industry: pig farming	-1.36E-01	1.54E+00	-0.089	0.929438	
s3	Primary industry: poultry farming	-1.49E+01	1.96E+03	-0.008	0.993943	
s3	Primary industry: other farmed livestock	-2.58E+00	1.42E+00	-1.816	0.069396	.
s3	Primary industry: arable farming	-7.95E-02	1.07E+00	-0.074	0.940855	
s3	Primary industry: vegetable production	3.43E-01	1.25E+00	0.275	0.782999	
s3	Primary industry: kiwifruit production	-2.76E-01	2.54E+00	-0.109	0.913228	
s3	Primary industry: wine grape production	-3.23E+01	1.73E+03	-0.019	0.985098	
s3	Primary industry: growing fruits, nuts, edible tree crops	3.94E-01	9.99E-01	0.394	0.693245	
s3	Primary industry: exotic forestry	-1.39E+00	8.45E-01	-1.642	0.100517	
s3	Primary industry: farm-based tourism	1.06E+00	1.25E+00	0.85	0.39556	
s3	Primary industry: other	1.56E+01	3.96E+03	0.004	0.996853	
s3	Land use: cattle	2.42E-01	2.95E-01	0.822	0.411148	
s1	Land use: dairy platform	-1.03E+00	1.07E+00	-0.962	0.33589	
s1	Land use: dairy runoff	-1.64E-01	5.71E-01	-0.287	0.773911	
s1	Land use: deer	-5.51E-01	7.09E-01	-0.777	0.437357	
s1	Land use: flowers	-1.29E-01	1.27E+00	-0.102	0.918701	
s1	Land use: forestry	2.31E+00	3.36E-01	6.879	6.05E-12	***
s1	Land use: forestry harvested	5.46E-01	8.39E-01	0.651	0.515249	
s1	Land use: fruit	-6.23E-01	6.74E-01	-0.925	0.354869	
s1	Land use: grain seeds	-1.41E+00	6.86E-01	-2.05	0.040335	*

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s1	Land use: grapes	1.67E+01	1.34E+03	0.012	0.990028	
s1	Land use: grazing	6.18E-02	3.73E-01	0.166	0.868158	
s1	Land use: hay	2.78E-01	3.00E-01	0.926	0.354459	
s1	Land use: kiwifruit	- 1.58E+00	2.20E+00	- 0.718	0.4726	
s1	Land use: other livestock	1.29E+00	5.55E-01	2.322	0.020216	*
s1	Land use: pigs	9.09E-01	8.27E-01	1.1	0.27154	
s1	Land use: poultry	-3.29E-01	9.04E-01	- 0.364	0.715963	
s1	Land use: sheep and beef	9.63E-01	3.77E-01	2.553	0.010682	*
s1	Land use: tourism	1.31E-01	7.76E-01	0.168	0.866209	
s1	Land use: vegetables indoors	-1.33E-01	1.20E+00	- 0.111	0.911427	
s1	Land use: vegetables outdoors	7.50E-01	5.97E-01	1.256	0.209152	
s1	Land use: wetlands	2.37E+00	3.79E-01	6.234	4.55E-10	***
s5	Live on farm: 12985	7.31E-01	4.08E-01	1.79	0.073491	.
s5	Live on farm: 12986	-1.75E-02	9.17E-01	- 0.019	0.984762	
	Null deviance: 716.11 on 606 degrees of freedom Residual deviance: 447.55 on 544 degrees of freedom AIC: 573.55 Number of Fisher Scoring iterations: 16					

Table S5b.

ID		Estimate	Std. Error	z value	Pr(>|z|)	
	(Intercept)	-2.5721	0.2198	-11.704	< 2e-16	**
s2	Has covenant on own land	1.1942	0.2721	4.389	1.14e-05	***
s1	Land use: forestry	2.0378	0.2534	8.043	8.80e-16	***
s1	Land use: sheep and beef	0.8600	0.2351	3.659	0.000254	***
s1	Land use: wetlands	2.2560	0.3162	7.134	9.71e-13	***
	Null deviance: 716.11 on 606 degrees of freedom Residual deviance: 516.36 on 602 degrees of freedom AIC: 526.36 Number of Fisher Scoring iterations: 5					

Table S5c.

		Estimate	Std. Error	z value	Pr(>|z|)	
	(Intercept)	-17.63091	3733.47905	-0.005	0.99623	
s7	Private land owners should protect habitat for native plants and animals on private land: 7	0.89451	0.46726	1.914	0.05557	.
s7	Private land owners should protect habitat for native plants and animals on private land: 8	0.46092	0.4822	0.956	0.33913	
s7	Private land owners should protect habitat for native plants and animals on private land: 9	0.72902	0.52367	1.392	0.16388	

s7	Private land owners should protect habitat for native plants and animals on private land: 10	0.28499	0.54286	0.525	0.5996	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 1	-2.75869	7515.56255	0	0.99971	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 2	-2.34739	4704.04145	0	0.9996	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 3	-1.4432	4589.15314	0	0.99975	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 4	15.94438	3733.47918	0.004	0.99659	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 5	11.02069	3733.47939	0.003	0.99764	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 6	14.45783	3733.47907	0.004	0.99691	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 7	13.80726	3733.47907	0.004	0.99705	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 8	14.07485	3733.47907	0.004	0.99699	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 9	14.58785	3733.47907	0.004	0.99688	
s8	The Department of Conservation should protect habitat for native plants and animals on public land: 10	14.65365	3733.47907	0.004	0.99687	
s4	Land ownership: myself	2.05938	0.86788	2.373	0.01765	*
s4	Land ownership: another individual	0.73929	0.49602	1.49	0.1361	
s4	Land ownership: family partnership	1.14743	0.5035	2.279	0.02267	*
s4	Land ownership: family trust	2.84305	1.60545	1.771	0.07658	.
s4	Land ownership: family company	-15.16504	2181.20979	-0.007	0.99445	
s4	Land ownership: māori trust / inc.	-0.32782	0.89255	-0.367	0.7134	
s4	Land ownership: corporate owned	0.80028	0.56051	1.428	0.15335	
s3	Primary industry: grazing livestock, not own	-1.00488	0.70147	-1.433	0.15199	
s3	Primary industry: farming sheep	-1.1933	0.69733	-1.711	0.08704	.
s3	Primary industry: farming beef	-0.63404	0.67011	-0.946	0.34405	
s3	Primary industry: dairying	-0.4815	1.32175	-0.364	0.71564	
s3	Primary industry: deer farming	-1.41502	1.65951	-0.853	0.39384	
s3	Primary industry: pig farming	-1.62701	1.72871	-0.941	0.34662	
s3	Primary industry: poultry farming	-15.77646	3237.32355	-0.005	0.99611	
s3	Primary industry: other farmed livestock	0.18893	1.12645	0.168	0.8668	
s3	Primary industry: arable farming	-0.6377	0.97659	-0.653	0.51376	
s3	Primary industry: vegetable production	-17.60586	1684.43689	-0.01	0.99166	

s3	Primary industry: kiwifruit production	-21.86036	1252.39174	-0.017	0.98607	
s3	Primary industry: wine grape production	0.31805	3547.36647	0	0.99993	
s3	Primary industry: growing fruits, nuts, edible tree crops	-2.61233	1.22786	-2.128	0.03337	*
s3	Primary industry: exotic forestry	-1.43336	1.10572	-1.296	0.19487	
s3	Primary industry: farm-based tourism	-0.30471	1.22571	-0.249	0.80367	
s3	Primary industry: other	17.84228	6522.63866	0.003	0.99782	
s1	Land use: bush	1.33585	0.31871	4.191	2.77E-05	***
s1	Land use: cattle	0.25264	0.32223	0.784	0.43303	
s1	Land use: dairy platform	0.04347	1.16905	0.037	0.97034	
s1	Land use: dairy runoff	0.56677	0.51588	1.099	0.27192	
s1	Land use: deer	-1.47072	0.90462	-1.626	0.10399	
s1	Land use: flowers	-16.51415	2108.4609	-0.008	0.99375	
s1	Land use: forestry	0.07809	0.34919	0.224	0.82305	
s1	Land use: forestry harvested	-0.40126	1.0045	-0.399	0.68956	
s1	Land use: fruit	0.18262	0.72978	0.25	0.8024	
s1	Land use: grain seeds	0.13595	0.58743	0.231	0.81699	
s1	Land use: grapes	-17.14267	3038.8154	-0.006	0.9955	
s1	Land use: grazing	0.09179	0.38977	0.235	0.81383	
s1	Land use: hay	-0.26423	0.32098	-0.823	0.41039	
s1	Land use: kiwifruit	4.42176	1.36611	3.237	0.00121	**
s1	Land use: other livestock	-0.26251	0.6334	-0.414	0.67855	
s1	Land use: pigs	0.75615	0.82544	0.916	0.35964	
s1	Land use: poultry	-1.45112	1.32678	-1.094	0.27408	
s1	Land use: snb	0.81476	0.41607	1.958	0.0502	.
s1	Land use: tourism	0.60351	0.86389	0.699	0.48481	
s1	Land use: vegetables indoors	-16.80093	1827.911	-0.009	0.99267	
s1	Land use: vegetables outdoors	-0.16404	0.70244	-0.234	0.81535	
s1	Land use: wetlands	1.02729	0.36046	2.85	0.00437	**
s5	Live on farm: 12985	-0.22256	0.46764	-0.476	0.63412	
s5	Live on farm: 12986	1.5973	0.97573	1.637	0.10162	
	Null deviance: 559.15 on 606 degrees of freedom Residual deviance: 396.01 on 545 degrees of freedom AIC: 520.01 Number of Fisher Scoring iterations: 17					

Table S5d.

		Estimate	Std. Error	z value	Pr(>|z|)	
	(Intercept)	-2.8859	0.2793	-10.335	< 2e-16	***
s1	Land use: bush	1.2523	0.2513	4.983	6.27e-07	***
s1	Land use: dairy platform	0.8408	0.3217	2.614	0.008960	**
s1	Land use: sheep and beef	0.7732	0.2875	2.689	0.007165	**

s1	Land use: wetlands	0.9950	0.2937	3.388	0.000703	***
	Null deviance: 559.15 on 606 degrees of freedom Residual deviance 484.38 on 596 degrees of freedom AIC: 494.38 Number of Fisher Scoring iterations: 5					

APPENDIX A. OVERVIEW, DESIGN CONCEPTS AND DETAILS PROTOCOL FOR LAND OWNER MODEL.

The following model description follows the ODD (Overview, Design concepts, Details) protocol for agent-based models (10, 11).

A1.1. Purpose

We designed and implemented the model to simulate collective conservation action on agricultural land, and to quantify the environmental outcomes of collective action with spatial landscape indicators (area and fragmentation of protected land). Specifically, the model allows us to investigate:

1) how the interacting effects of social network influences, actor attributes and ecological feedback influence collective, landscape-level conservation of native forest on agricultural land.

2) the mechanisms through which influence of behavioural factors in social actor's decision-making translates into changes in landscape structure. I.e., which behavioural factors, or combination of the factors included, frequently produce effective conservation action.

A1.2. Entities, state variables, scales

The model includes four types of entities:

1) Agents/individuals: land owners are social actors who make decisions about the protection of native or semi-natural habitat on their land. They are characterized by actor attributes (Table S1) and make decisions on whether their land (farm) is protected or not.
2) Agents/individuals: cross-scale actors are social actors who influence land owners connected to them. Cross-scale actors include representatives from indigenous groups (iwi), regional and district councils and central government. Cross-scale actors status does not get updated; their influence is always pro-conservation and affects directly only those land owners, who have (influential) links with cross-scale actors.
3) Spatial units: farms consist of multiple patches (grid cells) and represent area that each land owner has available for conservation, and upon which land user makes decisions. A farm can be in three states: protected, unprotected or covenanted.
4) Spatial units: all patches are additionally considered ecological spatial units, upon which natural habitat area and fragmentation indices are calculated. Connected protected patches are considered to create a non-fragmented habitat area. On the contrary, any non-protected cells between protected patches indicates the presence of habitat edges.

The variables characterizing these entities are presented in Table S1.

There are 200 social actors in the model, and the number of grid cells in the model arena is 841. Farms represent the land area that each land owner could set as protected natural habitat, and their sizes are standardized to give each land owner land proportionally to the size of their largest land parcel (in case a survey responder's farm consists of multiple blocks of land), self-reported in the survey. The model was run for 150 time steps, which represents 15 years of time.

A1.3. Process overview and scheduling

General model concept and simulations
The model is an agent-based model (12) integrated with the R environment (3), based on a new and detailed dataset on 600 rural decision-makers (1). The model consists of i) land owners and their social networks (two-mode network, i.e. including connectivity between land owners, and between land owners and cross-scale actors), and ii) a simulated landscape consisting of two layers: farms upon which each land owner makes decision to protect, covenant or not protect land, and an ecological landscape representing land as natural habitat or land in other use.

We ran one simulation for each parameter value combination for the two experiments including all behavioral factors, which resulted in 6561 simulations for homophily and random network each. Since the number of unique parameter value combinations were lower for the two other experiments including only social network influence (from land owners, i.e. excluding cross-scale actors) and actor attributes, we ran 80 simulations for each combination to gain 6561 simulations for the homophily and random network each. The model adjusts the assigned behavioural driver weights (presented in manuscript Table 1) to sum to one, and the simulations and result analyses are performed on the adjusted values.

For each simulation (Figure S3), a baseline system is set by drawing a subset of 200 individuals from a data set of 600 land owners, with their individual, self-reported actor attributes. A landscape is constructed with actor attribute data on ownership of natural habitats, covenanted land and farm size. During each time step, probabilities for protecting natural habitat are calculated for a subset (the percentage of land owners chosen for decision-making is included in parameter value settings, see Table 1) of land owners, who then either protect or not protect their land. For those not chosen for decision-making, we assume a decision to continue with their current behavior. If a land owner decides to protect their land, the farm is marked as protected area. If a land owner decides to stop protecting land, the land is marked as non-protected. Those land owners who have decided to protect land also have an option to covenant land, in which case that land cannot become unprotected during the entire simulation. During the following time step, decisions are made in an updated social-ecological context, since the landscape may have changed (natural habitat extent on neighboring farms affects decision-making through ecological feedback) as may have the behavioral status of network actors (land owners are affected by the habitat protection status of other land users they are linked to through social network influence). The model stops after 150 time steps. Model output (state) variables (Table S2) capture changes at the landscape-level in protected area extent, fragmentation and the duration of land as protected area, as well as number of land owners participating in conservation, and the detailed network structure of land owners' network.

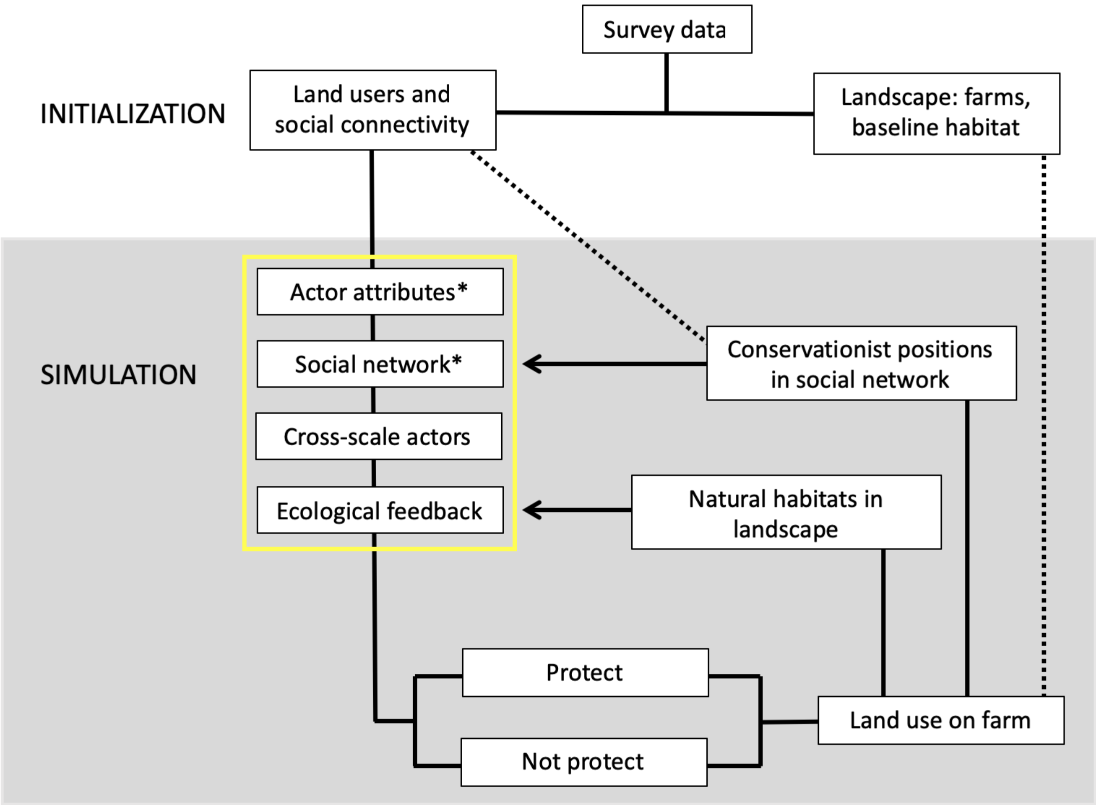

Figure S3. Model logic. Survey data is used in initialization to create land owners (including actor attributes), their network, and initial landscape. On the first time step of a simulation, social network influence and ecological feedback in decision-making are based on survey data; indicated with dashed lines. Yellow box marks decision-making based on behavioural factors. Based on influence from the behavioural factors, land owners decide to either protect or not protect land on their farm, potentially changing land use (i.e. protected/not) on farm. The extent of natural habitats on landscape-level emerges from land use on farms, and affects ecological feedback in decision-making during the next time step. Another social-ecological feedback is formed by social network influence, which is updated on each time step, as land use on farm determines which land owners in the network have protected natural habitats (here shortened to "conservationists"). Asterisks (*) mark the behavioural factors that are included in experiments including only two of the four factors, i.e. H_SNA and R_SNA.

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A1.4. NetLogo pseudocode

INITIALIZATION

Create land owner networks and calculate social network indices
Read in an input file with actor attributes for 600[3] survey respondents/land owners.
Create land owner agents by drawing a random subsample of land owners from actor attribute input file.
Define survey data actor attributes as land owner variables (see Table S1).

If Random Network or Degree Network generation is not chosen:
load homophily matrix from R environment
extract data for land owners from homophily matrix based on their ID
add network link between those land owners that are connected in homophily matrix, according to their self-reported indegree (e.g. number of incoming links)
set self-reported influence (converted to quantitative values: [0.33 0.66 1], non-influential links have value 0 and are not included) as link weights

If Homophily Network is not chosen:
ask land owners to create network links with other land owners in given probability
using Erdös-Rényi network generation
set [0.33 0.66 1] as link weight list
set network link weights randomly from link weight list

Export a list of IDs for land owners (i.e. social network actors)
Export weighted matrix of land owners network.
Social network analysis is performed in R environment, using mainly iGraph package (4).
Import network indices from R environment to NetLogo.

Create farms and landscape
Create as many farms as there are land owners.
Use survey data on normalized farm areas of the land owners to set the size of each land owner's farm. Set land owner ID as farm ID.
Cluster together all patches that belong to the same farm.
Mark adjacent farms to each farm as its 'neighbor farms'.
Fill landscape: while patches without farm ID, continue adding edge patches to farms.
Set patch colour the colour of the farm.
Set the colour of the patch as 'start patch colour'.

Set baseline native habitants
Land owners with native habitat on their land (survey data):
mark own farm as protected land.

[3] A subset of 3311 survey respondents. The subset of 600 land owners is a result of eliminating "Non-Applicable" - answers (mainly due to survey logic, occassionally because a responder has chosen to not reply to a specific question) from survey response variables used in the regression analyses.

Land owners with native forest on their land who have joined a conservation covenant (survey data):
    mark own farm as protected land, covenanted land, and as inconvertible.
Report baseline count of patches that contain native forest.
Report baseline count of patches that are part of covenant.
All other patches:
    set patches as not protected, not inconvertible, and not baseline habitat.

Decision-making set-up
Set values for 'land owner weight', 'actor attributes weight', 'iwi weight', 'council weight', 'central government weight' and 'ecological feedback weight' (the weights that each behavioural driver has on decision-making, see manuscript Table 1) according to the experiment-specific parameter values.
Adjust the total value of 'land owner weight', 'actor attributes weight', 'iwi weight', 'council weight', 'central gov weight' and 'ecological feedback weight' to sum to one.
Set parameter values for number Change-makers, i.e. the percentage of land owners able to change the conservation status of their farms on each time step, as well as 'Time steps', i.e. the number of ticks that land owners have to wait until next change of conservation status on their land.

EXECUTION

To go:

If time < stop time:

Update
Set patch colour 'start patch colour'
Set 'decision-makers' those land owners for whom 'minimum time since change' has passed or who have not changed the conservation status of their farm yet.

Calculate land owner network influence
Land owners with indegree > 0:
    let my 'habitat connections' be land owners that I have incoming link with and who have native habitat on their farms
    calculate the fraction of habitat connections of all my incoming links, both multiplied with link weights.
    set the fraction as my 'network influence'

Land owners with indegree = 0:
    set my 'land owner network influence' to 0

Calculate stakeholder influence
Land owners:
    set my 'indigenous group influence' my number of links to indigenous group multiplied with their link weight

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set my ‘council group influence’ my number of links to council representatives multiplied with their link weight

set my ‘central government group influence’ my number of links to central government representatives multiplied with their link weight

Set the highest indigenous/council/central government group influences among land owners as maximum indigenous/council/central government group influence among the land owners.

Land owners with indigenous group degree > 0 and indigenous representatives link weight > 0

set indigenous representatives influence as my indigenous group influence divided with maximum indigenous group influence

Land owners with iwi degree = 0 or iwi link weight = 0

set iwi influence 0

Calculate council and central government group influences for each land owner similarly to indigenous group influence.

Calculate actor attribute influence

Land owners:

set my actor attributes influence for protecting land and for covenanting land based on regression model (manuscript equation 4):

$$P(Y) = \frac{1}{1 + e^{(b| \quad |0 + b_{1i}X_{1i} + b_2X_{2i} + \dots b_nX \quad)}}$$

Calculate ecological feedback influence

Land owners:

set ‘my ecological feedback’ as a count of my neighbour farms with protected land divided with the count of my neighbour farms

Make conservation decisions

‘Decision-makers’:

set my ‘conservation probability’ as weighted sum of behavioural factors (*f*) and their parameter values (*w*) (manuscript equation 5)

$$P(conservation) = \sum_{j=1}^{n} w_j f_{ij}$$

Implement conservation action

If my ‘conservation probability’ is > random floating-point number 0-1
PROTECT NATIVE HABITAT
if my farm is not inconvertible
mark as protected land
change patch colour to white

‘Decision-makers’ without covenant barriers:
if my ‘covenant attributes’ > random floating-point number 0-1
if my farm is marked as protected land and is not inconvertible
JOIN COVENANT
mark land as inconvertible
set patch colour blue
Else:
UNPROTECT NATIVE HABITAT
If my farm is not inconvertible
mark as unprotected land
change patch colour to black

Update the conservation status of land owners and land
If land marked as protected
set land owner as ‘conservationist’
Else:
set land owner as ‘non-conservationist’
If land marked as covenant
set land owner as ‘covenant land owner’
Else:
set land owner as ‘non- covenant land owner’
Report the number of conservationists
Report the number of covenant land owners

Calculate the residence time of each farm as protected land
If patch colour white:
set ‘residence time’ as (‘residence time’ + 1)
If patch colour blue:
set ‘residence time’ as (‘residence time’ + 1)

Calculate habitat fragmentation indices (Modified from (13))

Identify contiguous groupings of patches with protected land as fragments (Modified from (13))
Mark patches that are not protected land to a group of its own.
Other patches: (loop)
select one protected land patch as a start of a new fragment
if a neighbouring patch is marked as protected land, assign it to the same fragment as a starter patch and mark as assessed

if a neighbouring patch is marked as protected land, assign it to the same fragment as a starter patch and mark as assessed

continue until all patches with protected land have been assigned into fragments

Calculate number and size of habitat fragments (Modified from (13))

Mark patches that are not protected land as a group of its own.

Label fragments with identification numbers

With each new fragment ID number, set 'fragment count' (fragment count + 1)

Set number of patches in each fragment as their area

Report fragment count and minimum and maximum fragment areas

Tick

If time = stop time:

Export habitat coordinates and social network data

Export a list of coordinates for each patch with protected land to R environment for calculating entropy

Export a list of IDs and conservationist status of land owners (social network actors) and weighted matrix of land owners network (optional, used for creating Figure S2 graph)

Calculate environmental outcome variables

Import entropy value from R environment

Report outcome variables, listed in Tables S2 and S4.

A1.5. Design concepts

A1.5.1. Basic principles

General concepts and hypotheses, and their relationship to the model:

- Biodiversity is affected by the abundance and spatial configuration of habitats on landscape level (14). The model investigates land owners' collective capacity to protect natural habitats on landscape-level and quantifies the environmental results with indicators describing the area and fragmentation of natural habitats on a landscape.
- Emergence (15): landscape-level area and connectivity of natural habitats in agricultural land is produced collectively by land use on farms, which, in turn, is a result of individual decision-making of land owners.
- Environmental outcomes of collective action may range from highly ineffective to successful (16). The output variables enable capturing the success of collective action.
- Pro-environmental behaviour can be encouraged with behavioural factors (17). Two to four behavioural factors are included in the study experiments.

- Multiple drivers effects are not necessarily additive, and the interplay between behavioural drivers and constraints may influence outcomes of collective action (16, 18). The model allows including several behavioural factors in decision-making and investigating the effects that the factors have in diverse combinations.

A1.5.2. Emergence
In the model, the macro-level environmental outcome (landscape structure) emerges from micro-level social interactions, i.e. individual decision-making and consequent farm-level land use and social network influence. The micro-level interactions are, in turn, affected by the macro-level environmental change (ecological feedback) and social diffusion (social network influence).

A1.5.3. Adaptation and objectives
The model includes heterogeneity in the social component, which allows land owners to have diverse objectives. Adaptation in a narrow sense is present in that land owners' decision-making takes into account changes in neighbouring farms. However, while land owners respond to changing conditions, seeking a specific individual or collective goal in their action is not included in the model.

A1.5.4. Learning
Not included

A1.5.5. Prediction
Not included

A1.5.6. Sensing
The external variables included in land owners' decision making are ecological feedback, which is theoretically based on land owners observing conservation action on neighbouring farms.

A1.5.7. Interaction
Land owners interact directly through static network links, and indirectly through social network and ecological feedback, when in effect.

A1.5.8. Stochasticity
Stochasticity is included partly to protect the identity of survey repliers, and partly to account for unknown factors in decision-making. The following processes are randomized:
- the location of each farm on the landscape
- the sample of 200 land owners from a pool of 600 surveyed land owners
- randomized network: an Erdös-Rényi randomized network model
- homophily network construction: which pairs of land owners are connected is partly random (due to unique samples of land owners for each simulation), see manuscript Methods and Materials section

A1.5.9. Collectives
The social community of the model is a conceptually a two-level network, in which land owners produce a layer one where they have links with each other as well as to the cross-scale actors. On the cross-scale actors' layer, links between cross-scale actors are not constructed, they have links only to the land owners.

A1.5.10. Observation
Data collected from model simulations is listed in Table S2.

State variables that are kept constant are:
- number of land owners
- actor attributes
- networks connections and link weights (networks are static during a simulation run, but positions in the network occupied by those who have protected land change according to land owner actions)
- time (number of ticks) until the model stops, i.e. each simulation runs for 150 time steps.

A1.5.11. Initialization
For each simulation (Figure S3), a subset of 200 individuals is drawn from a dataset of 600 land owners, with their individual, self-reported actor attributes. Land owners' network is created based on homophily matrix and actor attribute data, or network randomization. A landscape is constructed with actor attribute data on ownership of natural habitats, covenanted land and farm sizes. Initialization is described in detail in Pseudocode: initialization section.

A1.5.12. Input data
- Actor attributes: a table that includes 600 land owners and their actor attributes. Table S5 provides a sample of the table. The entire input file is available from Brown, P. on reasonable request
- Farm sizes: standardized (0 – 1) farm area of every land owner (Table S5)
- Homophily matrix (Table S6): a matrix that links land owners to each other according to their similarity, based on their actor attributes data. The values in the matrix are link weights that represent self-reported level of influence between land owners, and degree is self-reported in survey data.

A1.5.13. Submodels

The model's procedures and sub-models and summarized in Materials and Methods section in manuscript, Supplementary Materials Figure S3 and Appendix A section A1.4.: Pseudocode.

A2. MODEL EVALUATION
Parameter sensitivity analysis for the model is essentially performed as the main analysis of the study. The main results are presented in manuscript Figure 4. Suitability of the model for its objectives and validity of input data and model outputs are discussed in the manuscript in Discussion section (uncertainty and caveats).

Table S5. Model input data for actor attributes. A sample for 100 land owners available in [data depository link will be here in the final version (Sample_data2019.xls)] Temporary link for review:
https://www.dropbox.com/s/l99ockib7c3rvvo/Yletyinen_sample_data_LU1_2019.xlsx?dl=0

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Table S6. Homophily matrix. Example of homophily matrix that is used as an input data. [data depository link (HP_network.csv)] Temporary link: https://www.dropbox.com/s/em7zba0buydo1gu/HP_network.csv?dl=0

Table S7. Input data for calculating Gower's similarity. Actor attributes matrix used to create homophilous networks. [data depository link (Homophily.csv)] Temporary link: https://www.dropbox.com/s/czd7fj1xwfuffef/Homophily.csv?dl=0

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