

Emergent conservation outcomes of shared risk perception in human-wildlife systems

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Abstract

Human perception of risks related to economic damages caused by nearby wildlife can be transmitted through social networks. Understanding how sharing risk information within a human community alters the spatial dynamics of human-wildlife interactions has important

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implications for the design and implementation of effective conservation actions. We developed an agent-based model that simulates farmer livelihood decisions and activities in an agricultural landscape shared with a population of a generic wildlife species (wildlife-human interactions in shared landscapes [WHISL]). In the model, based on risk perception and economic information, farmers decide how much labor to allocate to farming and whether and where to exclude wildlife from their farms (e.g., through fencing, trenches, or vegetation thinning). In scenarios where the risk perception of farmers was strongly influenced by other farmers, exclusion of wildlife was widespread, resulting in decreased quality of wildlife habitat and frequency of wildlife damages across the landscape. When economic losses from encounters with wildlife were high, perception of risk increased and led to highly synchronous behaviors by farmers in space and time. Interactions between wildlife and farmers sometimes led to a spillover effect of wildlife damage displaced from socially and spatially connected communities to less connected neighboring farms. The WHISL model is a useful conservation-planning tool because it provides a testbed for theories and predictions about human-wildlife dynamics across a range of different agricultural landscapes.

人类-野生动物系统中共享风险感知产生的保护结果

【摘要】 人类对附近野生动物造成经济损失的风险感知可以通过社会网络传播。理解人类社会中共享风险信息如何改变人类与野生动物互作的空间动态，对设计和实施有效保护行动具有重要意义。我们开发了一种基于主体的模型，以模拟存在野生动物种群的农业景观中农场主的生计决策和活动（共享景观中的野生动物-人类互作）。在这个模型中，农场主根据风险感知和经济方面的信息来决定如何分配农作劳动、是否以及在哪里将野生动物驱逐到农场之外（如通过建围栏、挖沟渠或减少植被覆盖）。在农场主的风险感知受到其它农场主强烈影响的情况下，农场主普遍会驱逐野生动物，导致整个景观中野生动物生境质量下降，野生动物造成破坏的频率也下降。当遭遇野生动物造成的经济损失较高时，农场主对风险的感知会增加，从而导致他们的行为在时空上高度同步。野生动物和农场主之间的互作有时候也会产生溢出效应，使野生动物造成的破坏从社会及空间上紧密联系的社区转移到联系不够紧密的临近农场。本研究的共享景观中野生动物-人类互作模型是一种有效的保护规划工具，为不同农业景观中人类-野生动物动态变化的理论和预测提供了试验平台。**【翻译：胡怡思；审校：聂永刚】**
关键词： 基于主体的模型，共存，农场主的决策，建围栏，社会网络

Introduction

Co-occurrence between people and wildlife is expected to increase globally (Carter & Linnell 2016). Interactions in landscapes shared by human and wildlife populations can provide greater ecosystem services and assets to humans, including greater wildlife viewing or recreational hunting opportunities (O’Bryan et al. 2018). Likewise, some species benefit from the use of anthropogenic landscapes where high-quality food is consistently available (West et al. 2016). However, increasing encounters also introduce a range of risks to both wildlife and humans. Wildlife can eat people’s crops and livestock, damage property, and threaten human safety. Humans can, in turn, degrade wildlife habitats and kill animals they perceive as a risk (Chapron & Treves 2016). This negative perception of wildlife has put wildlife species at greater extinction risk worldwide (Ripple et al. 2014). Policies to enhance wildlife conservation are in place in many shared landscapes, but they often do not have the expected impact and in some cases have unintended consequences, such as actually increasing risks from wildlife to humans (Carter et al. 2017). These unintended consequences can occur when key social and ecological processes, and their feedbacks, are overlooked (Carter et al. 2014). Often ignored is how individual decisions to manage conflict in a given location (e.g., lethal or nonlethal deterrence of wild carnivores) influence human-wildlife interactions in other locations, such as displacing risks from wildlife to new areas. We addressed these challenges by incorporating theories of human risk perception into a spatially explicit, agent-based model (ABM) that simulates human-wildlife interactions on shared agricultural landscapes.

A number of individual-based theories of human risk perception exist, and some have been formalized in ABMs to simulate interactions in social-ecological systems (Schlüter et al. 2017; Magliocca & Walls 2018; Baeza & Janssen 2018). Such theories emphasize the effects

of risk perceptions on individual economic decisions, cognitions, and emotions. Several studies, however, show that risk perception is not simply an individual cognitive mechanism, but also depends on relational aspects of individuals and their networks of influence (Scherer & Cho 2003; Muter et al. 2013). The stronger the tie between two actors in a network, the more likely they are to adopt similar attitudes and behaviors. Because wildlife-related risks can be contentious or highly salient, one would expect that interactions with wildlife generate a great deal of interpersonal discussions (e.g., information flow) about those events and facilitate transmission of risk information throughout a community (Muter et al. 2013).

Although there is growing recognition of the influence of social connections on risk perceptions within a community (Scherer & Cho 2003; Muter et al. 2013), the role of space in mediating the outcomes of socially shared risk perceptions has received little attention. Yet, many risks are spatially heterogeneous, such as the location of floods or crop damage from herbivores. Risks that vary in space likely intersect with one's social network, such that farmers who experience a risk will likely share information about it with others in a similar environmental context. Individual perceptions can directly relate to an individual's behaviors (Bruskotter et al. 2015). Therefore, one would expect that network-propagated risk perception as a function of spatial proximity can give rise to spatially nonrandom behaviors in human communities. On one hand, these behaviors can represent an effective community response to environmental hazards, such as fire or flood. On the other hand, spatially heterogeneous human behaviors can also have significant consequences on wildlife populations when they involve human-caused mortality (e.g., population sinks) or habitat fragmentation (e.g., forest clearing for farms).

Investigating social-network influences on risk perception and the emerging spatial patterns in coupled human-wildlife systems is much needed. However, obtaining the requisite empirical evidence is extremely challenging, and no studies to date have simultaneously investigated these processes. To help fill this knowledge gap, we developed WHISL (wildlife-human interactions in shared landscapes), an agent-based model that simulates human-wildlife interactions in stylized social-ecological conditions. Specifically, WHISL simulates individual farmers' livelihood decisions and activities in an agricultural landscape shared with a population of a generic wildlife species. Individuals of the wildlife population occasionally damage the farms (i.e., costs associated with crop loss or livestock depredation) and the farmers may respond to these encounters by excluding wildlife from their farms (e.g., through fences, trenches, or vegetation thinning). These farmer decisions are modulated by shared risk perception from other farmers. The goal of the model is therefore to explore the patterns that emerge from the behaviors (e.g., perception, learning, adaptation, selection, action) of the farmers and the spatial configuration of the landscape (Fig. 1a).

We had 2 objectives: describe how risk perception mediates farmer responses to and negative impacts of wildlife encounters under different spatial and social network scenarios and, based on these scenarios, generate hypotheses about the causal mechanisms producing different outcomes to be tested against empirical data. We used WHISL to test three main hypotheses: greater social transmission of risk perception leads farmers to invest in efforts to exclude wildlife from their farms, regardless of whether those farmers have directly experienced wildlife damage; the greater the social transmission of risk perception the greater the spatiotemporal synchronicity among farmers to exclude wildlife from their farms; and although high levels of social transmission of risk perception may lead to overall lower frequencies of wildlife damages across the landscape, farmers who are disconnected from the

social network experience greater likelihood of wildlife damage than those who are connected to the social network because wildlife are pushed off other farms (i.e., spillover effects). By experimentally testing these hypotheses, we sought to explore how, where, and when certain mechanisms are dominant and the effects of those mechanisms on human livelihoods and wildlife management. The insights from WHISL can, therefore, shed light on processes that enhance human-wildlife coexistence under uncertain and changing social-ecological conditions.

Methods

The 3 main elements of WHISL are the agents and their attributes and actions; the attributes of the shared landscape; and farmer's decision-making process, the formulation of risk perception, and its relation to spatiotemporal propagation of risk. Information about the mathematical details of the model are available in Supporting Information, and model source code is available in a public repository (see below).

Model agents

The WHISL model included 2 types of agents: farmers and wildlife. Each farmer j ($j = \{1, \dots, J\}$) was the owner of a subset of cells in a landscape called the farm F_j . Each farmer had as attributes, a time-varying perception of risk of encounters, $\pi_{j,t}$, and the amount of labor available, L^T_j . Farmers obtained an income from agricultural production of a good with a price determined by an external market, and off-farm wages (Supporting Information).

In each annual cycle, farmers decided the amount of labor to invest in agriculture, the cells they needed to designate to agriculture production, and how much labor they needed to invest in excluding wildlife from their land (Fig. 1a). Each farmer has an aspirational level that determined an income target (Supporting Information). The income target was used to decide how much labor to invest in agriculture (decision 1). Each farmer shared information about the risk of encounters with other farmers in a spatially structured social network. Farmers also remembered past encounters with wildlife. The combination of a farmer's own past experience and the experience shared from other farmers was used to reevaluate the perception of risk. The risk perception was subsequently used by the farmer to decide to either exclude wildlife (e.g., through fencing) or designate more land to production or not invest in agriculture at all (decisions 2 and 3). Investing in excluding wildlife at a given farm cell in turn reduced its availability, $a_{l,t}$, to wildlife (i.e., wildlife cannot access that cell). The decision-making algorithms and procedures to simulate farmers' decisions were based on prospect-theory principles (Kahneman & Tversky 1979) and on the literature of spatiotemporal perception of environmental hazards (Viscusi 1991; Gallagher 2014). From the model simulations, we obtained the total number of wildlife encounters for each farmer, the total wealth and average income of each farmer, and the total available land to wildlife on each farmer's farm.

The model also included wildlife individuals from a population of size N . Wildlife agents' sole attribute was their position in the landscape, and their only behavior was movement. Their location in the landscape was updated using a simple stochastic procedure in which one cell was chosen from a subset of cells in a von Neumann neighborhood of predefined radius. The probability of a cell being chosen to move to was proportional to the attractiveness of the

cell to the wildlife, which depended on the quality of the cell to support wildlife, q_l , and its availability.

Shared agricultural landscape

A landscape $\Gamma = \{1, \dots, l, \dots, l_{\max}\}$ was composed of a set of square grid cells of the same size. Each cell was characterized by the productivity of the land, γ_l ; the quality of the cell to support wildlife q_l ; and the availability of the cell for the wildlife. The productivity of the land was defined as the maximum possible yield a farmer could obtain from the cell (Supporting Information). Habitat quality represented the primary productivity of the land to support wildlife, which in turn affected the attractiveness of the cell. The availability of the land to wildlife depended on the decision of farmers to exclude wildlife from all or portions of their farm. The availability of a farm cell varied in time as a function of farmers' decisions to invest in excluding wildlife from that cell and the rate at which the effectiveness of the exclusion measure decayed, d . For example, fences will degrade over time if not maintained.

Farmer decisions

Given the maximum possible yield on their farm and exogenous information about prices, costs, and off-farm wages, farmers decided how much labor and to which of their farm's cells to invest in farming and from which of the farmed cells to exclude wildlife. Labor allocation was based on past gains and an aspirational target. The expected gain in each cell was calculated under uncertainty in potential losses due to encounters with wildlife agents.

Land-use outcomes were modeled as the result of each farmer's annual labor allocation decisions, the rules for which were derived from smallholder household economic theories (Netting 1993) and implemented in Magliocca et al. (2013, 2014). We assumed that the total

labor needed was proportional to the farm size, $|F_j|$. Labor allocated to agriculture was adjusted each decision cycle to meet an aspirational target income (including production for subsistence). Target income was defined as a moving-average reference point, set to 80% of past earnings (Bert et al. 2011). Expected income from agriculture was calculated by farmers considering information about land production, prices, labor and production costs, and the perception of risk and damage from wildlife. Land was then allocated for agricultural production to meet the agricultural portion of income aspirations. For example, a farmer might produce more crops than were needed for own consumption in a given year and reduce the amount of labor allocated to agriculture in the subsequent year to minimize labor in production and risk of losses; and vice versa (e.g., decreasing food stocks result in increased farm labor). Given farm-level expected income and income aspirations, annual labor for agriculture was allocated and total land under production was defined. Once total labor was allocated, each farmer selected a subset of farm cells that maximized return based on agricultural productivity and varying production costs. In addition, the farmer decided if the action of excluding wildlife would maximize returns net of construction and maintenance costs.

Substantial empirical evidence from natural-hazards research suggests that individual risk perceptions are biased, or subjective (Ludy & Kondolf 2012), and risk perceptions change over time as new risk information is presented through either direct experience of hazards or indirect information channels (Magliocca & Walls 2018). Acknowledging the socially constructed nature of risk (Kahneman et al. 1982; Slovic et al. 2007), we defined *objective risk* as the probability of a hazard event based on directly measurable causal factors. In this context, objective risk was calculated as the probability of a wildlife agent's presence at a given time and location based on model parameters of habitat quality and the density of

wildlife agents in the landscape. We defined *subjective risk* as the expected probability of an event based on both direct and indirect (e.g., socially communicated) experiences with hazard events. Thus, subjective risk perception may diverge from and be compared with the objective probability of a hazard event in response to the number and frequency of events over time. In particular, risk perception may undergo large and immediate changes after a hazard event (Gallagher 2014). A common Bayesian learning model (Viscusi 1991) provides a formalization of dynamic risk perception in which an individual observes the occurrence of a hazard event and updates their expected probability of future events (Davis 2004). Further, additional empirical evidence demonstrates that risk perception diverges from objective levels over time and the rate at which it diverges varies in relation to time since a hazard event (i.e., time weighting [Gallagher 2014]).

Following the time-weighting formalization by Gallagher (2014), we developed a farmer subjective risk perception of detrimental wildlife interactions that was a function of the expected frequency of encounters, the time-horizon for remembering past events, and the risk perceptions of other farmers' within the given farmer's social network. Farmers were assumed to have prior information about the average risk of encounters per cell based on the quality of the land to support wildlife, the available area to wildlife, and the wildlife population size. We assumed that farmers give more attention to encounters that occurred more recently and share risk information with their social network.

Each farmer shared information about risk perception with a subset of other farmers connected in a social network. Only the most salient information was shared through the social network, which we assumed was information limited to only negative encounters with wildlife. In the model, a farmer's network was formally defined by the graph $G_j = (\Psi, E)$,

where Ψ is the subset of farmers connected to farmer j and E is the link between farmers.

The topology of the network was defined based on a distance-weighting function between farmers, such that 2 farmers that were close in space were more likely to share a link. We used the concept of “ego-network topology” to represent the extent of the social connections that each farmer shared information with (Everett & Borgatti 2005). Generally, the ego-network of a farmer, j , had a group of first- and second-degree connections we defined as G_j^1 and G_j^2 respectively. Using this network, the perceived risk sensed by farmer j was defined as

$$\pi_{j,t}^{SN} = w_1 \pi_{j,t} + w_2 \max_{g \in G_j^1} \pi_{g,t} + w_3 \max_{g \in G_j^2} \pi_{g,t},$$

with

(1)

$$w_1 + w_2 + w_3 = 1.$$

All experiments were simulated on a 100 x 100 landscape 10 times to capture the variation in wildlife distributions, damages, and habitat quality. Two landscape scenarios were explored by manipulating the spatial structure of the agricultural productivity, γ_l , and quality for wildlife. The first scenario was a mixed landscape, where each cell was randomly assigned a value for agriculture productivity and wildlife quality with a uniform random number generator (Fig. 1b). The second scenario was the protected area or gradient landscape, where the agricultural productivity and the quality for wildlife both were gradually varied from east to west, but in opposite directions. That is, as γ_l increased from east to west, q_l decreased from east to west (Fig. 1b). We tested two social scenarios. First, farmers formed risk perceptions by placing more combined weight on information from their social network than their own experiences (i.e., $w_1 \ll w_2 + w_3$), high social influence. Second, T farmers formed risk perceptions by weighting their own experiences more than socially transmitted risk information (i.e., $w_1 \gg w_2 + w_3$), low social influence. We performed a sensitivity analysis to evaluate the effect of parameters with high uncertainty. The sensitivity analysis was

conducted to assess the degree to which model outcomes changed when we varied several key parameters: distance between houses (min_dist), size of farms ($|F_j|$), the price per unit of yield (p), and damage from wildlife per encounter (δ) (Supporting Information).

Results

Synchronicity in human decision making

Farmers who were part of a spatially proximate social network were more likely to behave the same way (i.e., exclude wildlife) in both space and time (Fig. 2) than farmers who were not part of such a network. Thus, the more the risk was shared among the social network, the more likely those farmers behaved identically in response to the risks. In the mixed landscape, even with low social network influence, the landscape pattern generated clusters of risk from wildlife that facilitate synchronous behaviors by farmers to exclude wildlife from their farms (Fig. 2a). This synchronicity was substantially elevated when the level of social network influence was high. In the mixed landscape, the correlation extended to 30 cells, or almost one-third of the entire landscape (Fig. 2a). However, in the protected-area landscape with low social network influence, the degree of correlation among farmers to exclude wildlife was near zero, indicating that landscape patterns of risk and social sharing of risk perception were not concentrated in space and time (Fig. 2b).

Human-wildlife interactions across agricultural landscapes

In general, the average number of wildlife encounters per farmer gradually decreased as damage levels increased, corresponding to the declining area available to wildlife due to farmers excluding them from their farms (Fig. 3). The spatial structure of the landscape and level of social influence augmented this overall trend. In the simulation experiments with the mixed landscape, available habitat for wildlife (i.e., not excluded) and the average number of

encounters per farmer were lower when social influence was high (Fig. 3a, c), and increasing damage per wildlife encounter amplified these relationships. For example, available habitat decreased by approximately 70% across the range of damage levels when social influence was high, compared with only 20% when social influence was low (Fig. 3a). As damage levels increased, the average number of encounters per farmer in the mixed landscape decreased by approximately 50% (Fig. 3c). Decreases in available habitat and encounters also decreased in protected area landscape when social influence was high, although the degree of change was much less pronounced (Fig. 3b, d). Moreover, average farmer income did not differ between low or high levels of social network influence, independent of landscape configuration (Supporting Information). Nor did income change with increasing damage levels, suggesting that farmers in all simulation experiments were successfully maintaining income by excluding portions of their farms to wildlife in response to increased damage.

Spillover effects on disconnected farmers

When social network influence was high, farmers excluded more of their farms from wildlife as the number of connections to neighbors increased (Fig. 4a, b). This pattern was amplified in the mixed landscape, in which farmers with 15 connections were using exclusionary measures about 8 times more often per year when social influence was high than when it was low (Fig. 4a). Overall encounters per year were higher in the mixed landscape than the protected area (Fig. 4c, d), indicating that the mixture of agricultural productivity and habitat quality provided more opportunities for encounters. Farmers in the mixed landscape with <5 connections experienced a greater number of encounters per year when social influence was high compared with when it was low; completely disconnected farmers experiencing almost 3 times as many (Fig. 4c).

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Holding constant the initial habitat quality of farmers' locations and their social network connections, any changes in the number, timing, or location of wildlife encounters was an emergent outcome resulting from farmers' responses to wildlife encounters and altered wildlife movements resulting from farmers' responses. Although a large portion of farmers in the mixed landscape had less overall number of encounters with wildlife when social influence was high compared to low (Supporting Information), some farmers were more likely to experience much greater number of encounters (i.e., over 40). In contrast, all the farmers in the protected-area landscape experienced fewer encounters with wildlife when social influence was high than when it was low (Supporting Information). As social influence increased, wildlife encounters disproportionately increased for farmers with low initial habitat quality and low social connections. This was illustrated by a shift toward the upper-right quadrant in the (log) mean values of encounters between high and low social influence scenarios in the mixed landscape (Fig. 5). In contrast, the shift in (log) mean encounters to the lower-left indicated the opposite effect in the protected area landscape, suggesting that excluding wildlife did not demonstrably displace encounters to other farms in a spatially structured landscape (Fig. 5).

Discussion

We found evidence that socially transmitted risk perception created a feedback between wildlife and human behaviors. Notably, disconnected farmers in the mixed landscape incurred greater damage from wildlife displaced from well-connected farms (Fig. 4c). This is because well-connected farms effectively, and synchronously, excluded wildlife from large portions of their farms to create a spillover effect on disconnected farmers. Several empirical studies have alluded to similar spillover effects. A recent study showed that, despite the challenges associated with maintenance responsibility and costs, fencing designed to mitigate

human-elephant conflict on the border of Kenya and Tanzania could bring immediate, localized relief from crop losses by African elephants (*Loxodonta africana*). However, connectivity models indicated that the fencing could shift the regional patterns of elephant habitat use, potentially displacing conflicts to new agricultural areas (Osipova et al. 2018). Another study in Kenya around Nairobi National Park showed that the use of LED flashlights on bomas displaced lion (*Panthera leo*) depredation toward bomas without the flashlights (Lesilau et al. 2018). In Alberta, Canada, and Idaho, United States, the use of fladry barriers (flags hanging from ropes) on some ranches likely shifted depredation by wolves (*Canis lupus*) onto neighboring ranches that did not use fladry (Musiani et al. 2003). In Norway, Asheim and Mysterud (2005) reassessed data on sheep losses to conclude that when livestock-guarding dogs had prevented predators from hunting a particular area, the predators switched locations to prey on domestic sheep in another area. Unanticipated consequences such as these could diminish local support for conservation actions. Thus, there is a need and opportunity for future work on spatial spillover effects in human-wildlife systems.

In addition to socially transmitted risk perception, our model indicated that the spatial configuration of farms and wildlife habitat strongly influences the dynamics of human-wildlife interactions. The two configurations we used in the model generally correspond to landscapes that are shared (i.e., mixed landscape experimental setup) or spared for wildlife (i.e., protected area experimental setup). The importance of these 2 landscape configurations is a major topic in conservation now because they have implications for spatial zoning, land use, and animal-dispersal corridors (Luskin et al. 2018). For example, in northern Tanzania, elephants use small farms as “stepping stones” between the refuges and contiguous farmland increased habitat connectivity for elephants (Pittiglio et al. 2014). However, in Gujarat, India, shifts in agricultural patterns led to a significant increase in the livestock being killed by lions

and leopards (*Panthera pardus*). As a result, more of those predators were found dead in farmlands, presumably killed by farmers, during that period of time (Vijayan & Pati 2002). Importantly, it was in the mixed landscape that we observed the largest spillover effect of wildlife damages onto farmers that were disconnected from the social network. Examining human-wildlife dynamics on mixed landscapes warrants more attention as many wildlife species range well outside of protected areas (Carter & Linnell 2016). Furthermore, the Aichi Biodiversity Target 7 of the Conservation of Biological Diversity stresses that lands used for agriculture also be compatible with biological conservation (Convention on Biological Diversity 2010). However, to date, very little work has integrated human-wildlife conflict into discussions on the relative benefits of land-sharing approaches (López-Bao et al. 2017; Crespin & Simonetti 2018).

We also found that socially transmitted risk perception influenced the degree to which human behaviors in response to wildlife are spatiotemporally correlated. This has implications on conservation outcomes. Tightly knit communities that share information instantaneously through cellular phones, for example, might exhibit behaviors in which there is a widespread and rapid response to wildlife. Although such responses could be detrimental to wildlife, such as the illegal killing of protected species (Chapron & Treves 2016), they could also be used to help spread pro-conservation behaviors, particularly if such behaviors are also linked with improved livelihood and wellbeing measures. For example, virtual geofences provide near real-time information about approaching carnivores to those livestock owners participating in the program (Weise et al. 2019). Livestock owners in that network can therefore rapidly place their livestock in corrals, helping reduce livestock depredation and retaliatory killing of carnivores.

Farmers in the model could only respond to wildlife damage by excluding wildlife from their farms. A primary way to do that is through fencing, a common practice that is a contentious issue in conservation. On one hand, fences might be the best way to mitigate human disturbance and human-wildlife conflicts for certain species, such as lions (but see Creel et al. 2013; Packer et al. 2013). On the other hand, fencing is associated with detrimental impacts, such as edge effects on wildlife in protected areas (Massey et al. 2014) and disrupting important migration routes (Linnell et al. 2016). As a first pass, our model provides an experimental environment to simulate and explore interactions between individual economic decisions under risk, social processes of risk communication, wildlife movement, and landscape structure. Such an experimental environment enables interrogations of complex socioecological processes, such as identifying places where fences are more likely to be erected and maintained and potential consequences for regional human-wildlife interactions. In addition, the model allows testing different hypotheses about network topology and rates of information flow in space and time (e.g., spatially proximal to spatially distal, rapid, or delayed).

Several factors not included in our model, or only examined in a limited context, could be explored in future iterations. These include the valuation and the degree of trust among landowners, policies that limit or facilitate farmer activities, dynamic markets, and the behavioral and ecological attributes of the wildlife species interacting with farmers, among others. Including other human responses to wildlife, especially lethal removal would also expand the utility of the model. The social-psychological factors motivating an individual's decision to kill an animal in order to reduce risks have been the subject of much recent literature (Chapron & Treves 2016; Carter et al. 2017; St. John et al. 2018). Understanding the social, spatial, and policy processes that influence those decisions can have profound

implications on wildlife conservation. Indeed, if lethal control were to exhibit similar levels of spatiotemporal synchronicity in farmer behaviors in our model that could create wildlife population sinks and threaten their long-term persistence. Similarly, noneconomic motivations, such as cultural values and norms or other forms of ecological knowledge, are known to influence farming household decision making (Huber et al., 2018). We excluded such influences on farmer decision making for the sake of simplicity, but values or norms for or against wildlife deterrence (e.g., fencing) or ecological knowledge of unintended consequences of various deterrence actions could introduce another source of spatiotemporal synchronicity.

The model also substantially simplified wildlife population dynamics because we assumed the population size remained constant throughout the simulation. This model design choice was made for two reasons. First, maintaining the wildlife population facilitated isolation and attribution of changes in human-wildlife encounters stemming from spatial and social processes of risk perception and farmer behavior alone. Although wildlife population dynamics are undoubtedly important, this simplification greatly eased the interpretation of already complex model behavior. Second, in the current model version, wildlife population dynamics were omitted to maintain generality, but variations in population dynamics and other important characteristics (e.g., range size and mobility) will be explored in future model applications.

This work underscores the importance of collecting geospatial attributes of social norms and networks to validate the model structure and examine how different social-ecological conditions may limit or facilitate human-wildlife encounters (Bullock et al. 2018). Studies on human-wildlife interactions are increasingly calling for coordinated collection of social and

ecological data (Carter et al. 2014; Lischka et al. 2018) to reveal important causal relationships that might affect conservation. For example, a recent study in Sumatra indicated that integrated social-ecological models yielded predictions of human tolerance to tigers that were 32 times better than models using social predictors alone (Struebig et al. 2018). The authors argue that using these models to preemptively direct interventions would have averted approximately 50% of tiger attacks on livestock and people and saved 15 tigers from retaliatory killing (Struebig et al. 2018). However, collecting sufficient social and ecological data to make predictions is time and resource intensive. In the absence of sufficient empirical data, our model provides a means for addressing these challenges. Social and ecological theories can be integrated and interrogated to tease out key variables and causal relationships influencing human-wildlife interactions, which supports more targeted data collection efforts to test hypotheses about mechanisms producing specific feedbacks and emergent outcomes.

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Supporting Information

Detailed model description (Appendix S1); relationship between income and damage, relationship between number of farmers and number of encounters, and relationship between land available to wildlife and crop prices, distance between farmers, farm size, and farmer social connections (Appendix S2); and details on farmer state variables and parameters for numerical scenarios and additional references (Appendix S3) are available online. The authors are solely responsible for the content and functionality of these materials. Queries

(other than absence of the material) should be directed to the corresponding author. Model source code is available from <https://www.comses.net/codebase-release/f142ddf1-c653-40b0-9fe6-29f91d80cf79/>.

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Figure Captions

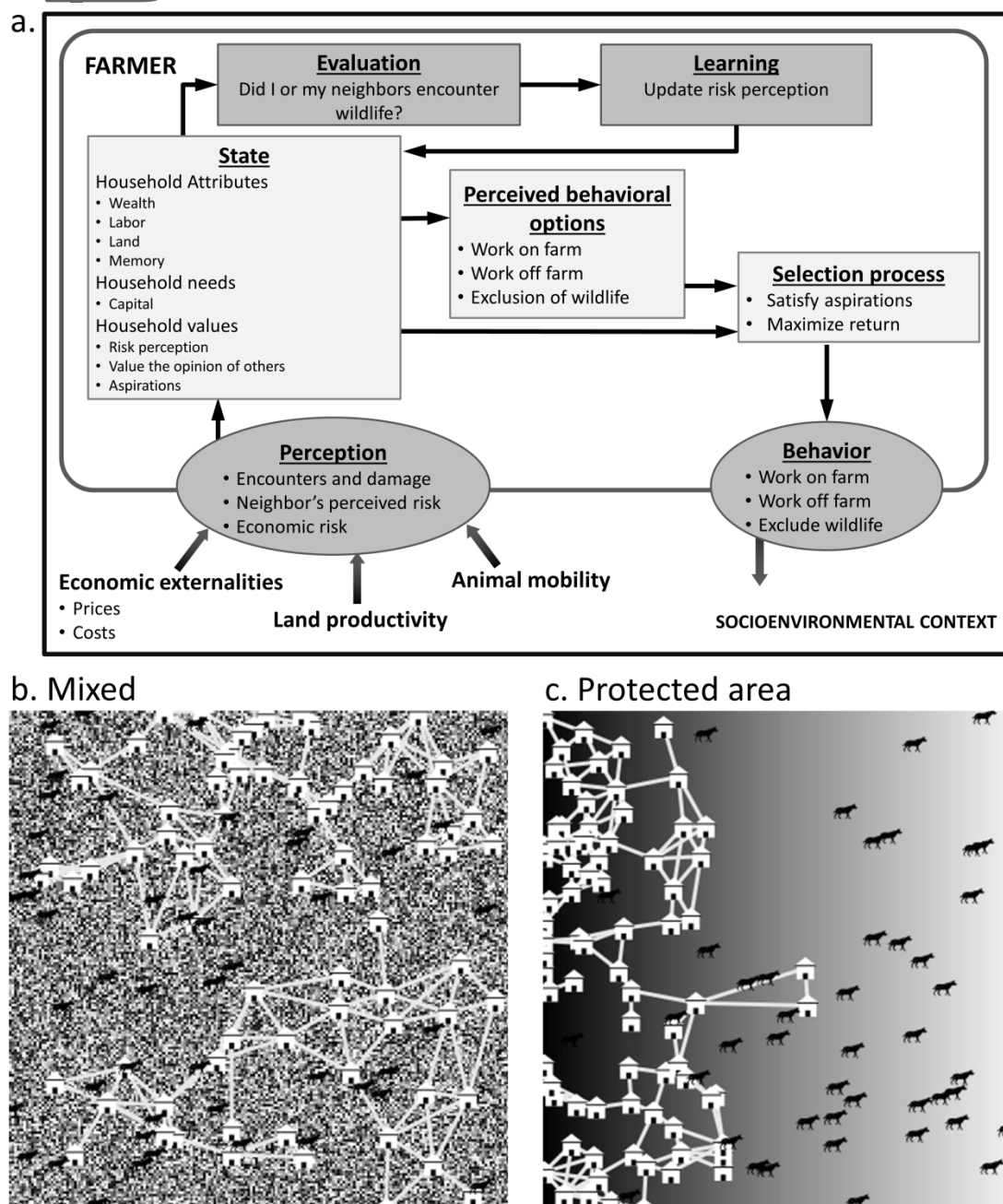


Figure 1: Diagram of human-behavior modeling showing (a) key components of an agent-based model of wildlife-human interactions in shared landscapes (WHISL). Model interface for the (b) mixed landscape and (c) protected area show low- (dark shading) to high-quality

wildlife habitat (light shading) in the background and the location of farmer households (house icons) and their connections to each other (lines).

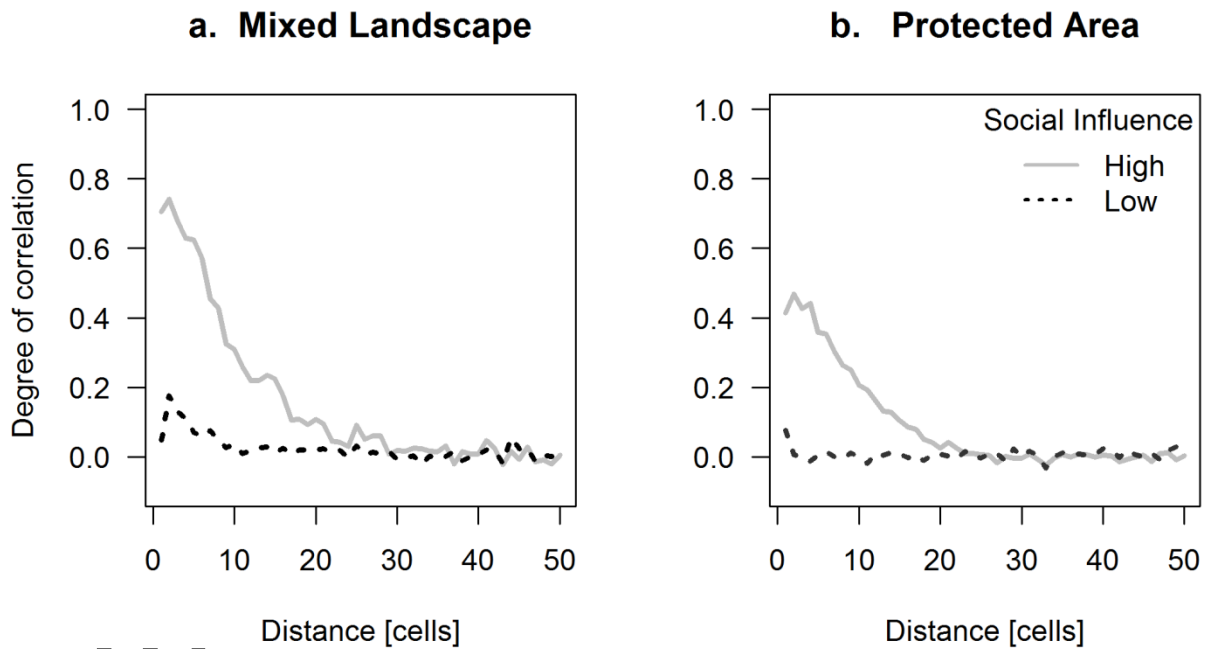


Figure 2: Model results showing the degree of spatiotemporal correlation in fencing behaviors by farmers for the (a) mixed and (b) protected-area landscapes for simulations with high (solid line) and low (dashed line) social influence among farmers. Distance was measured as cells in the landscape.

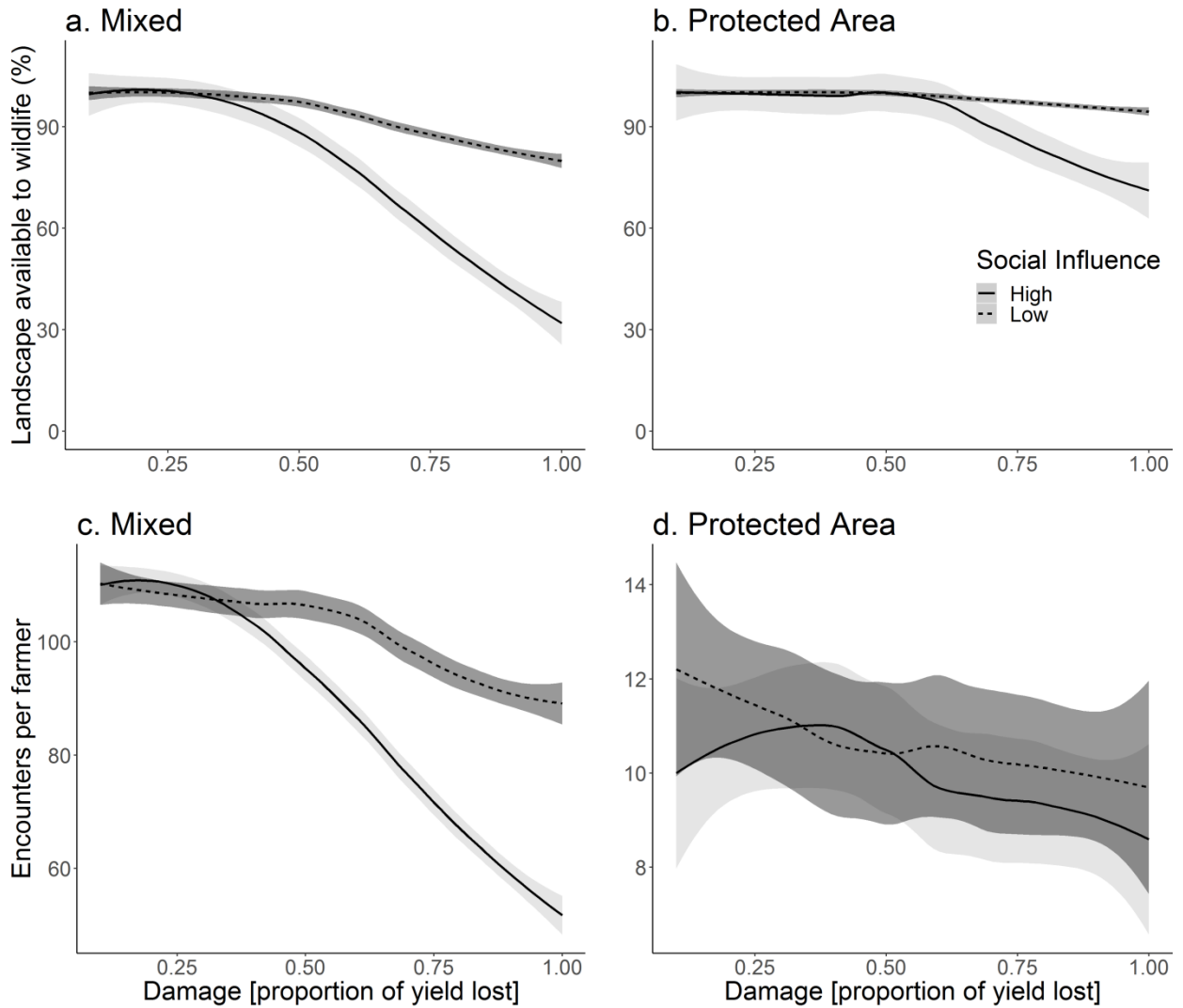


Figure 3: Percentage of the landscape available to wildlife and encounters with wildlife per farmer as damage per encounter with wildlife increases (lines, mean of 10 iterations for each parameter combination; shading, 95% CI). Each outcome was compared between simulations with high (solid line) and low (dashed line) social influence and between the mixed (a, c) and protected-area (b, d) landscapes.

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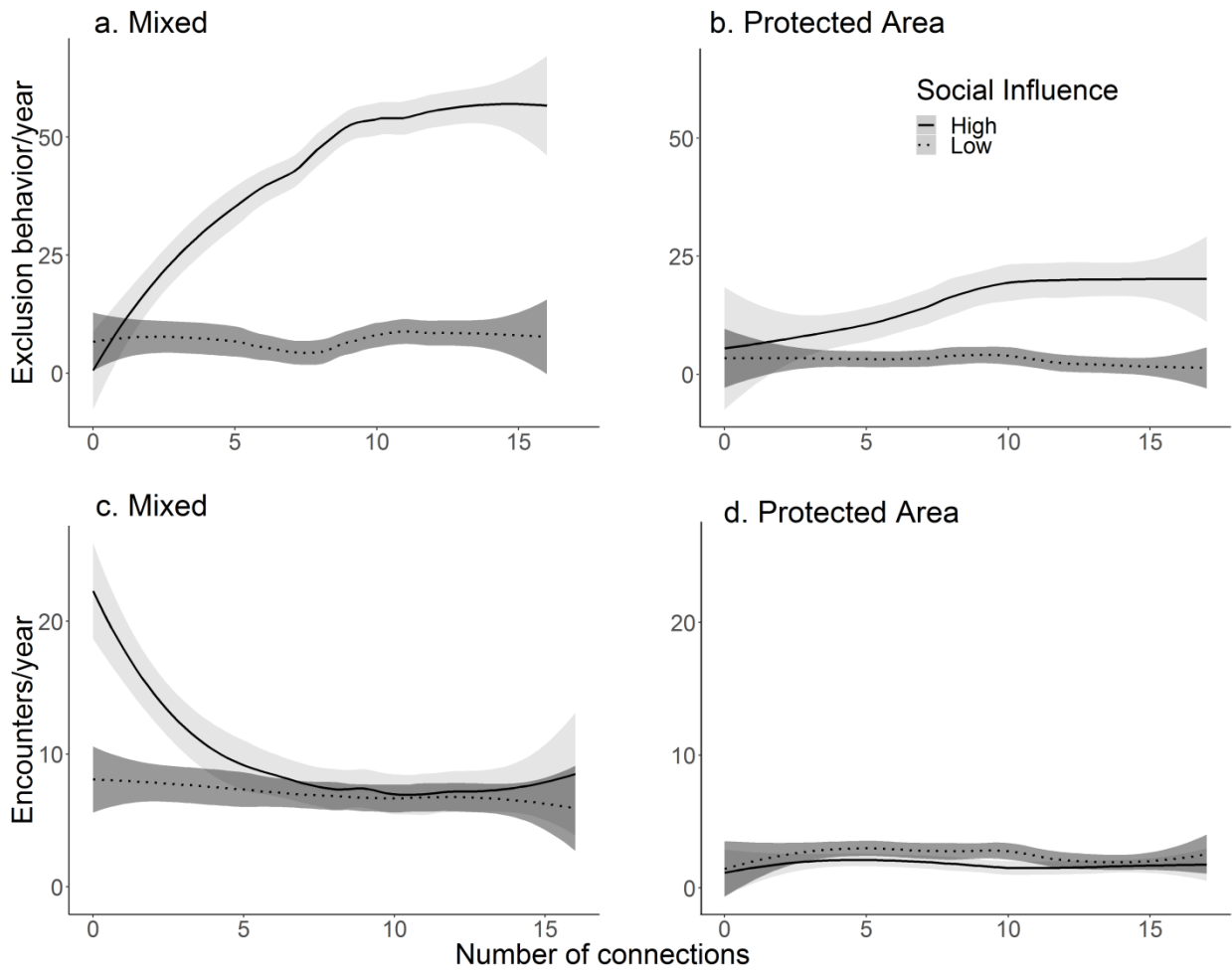


Figure 4: Number of wildlife exclusion behaviors and encounters per year for farmers with varying levels of connections to others in their social network. Each outcome was compared between simulations with high (solid line) and low (dashed line) social influence and between (a, c) mixed and (b, d) protected-area landscapes (lines, mean of 10 iterations for each parameter combination; shading, 95% CIs).

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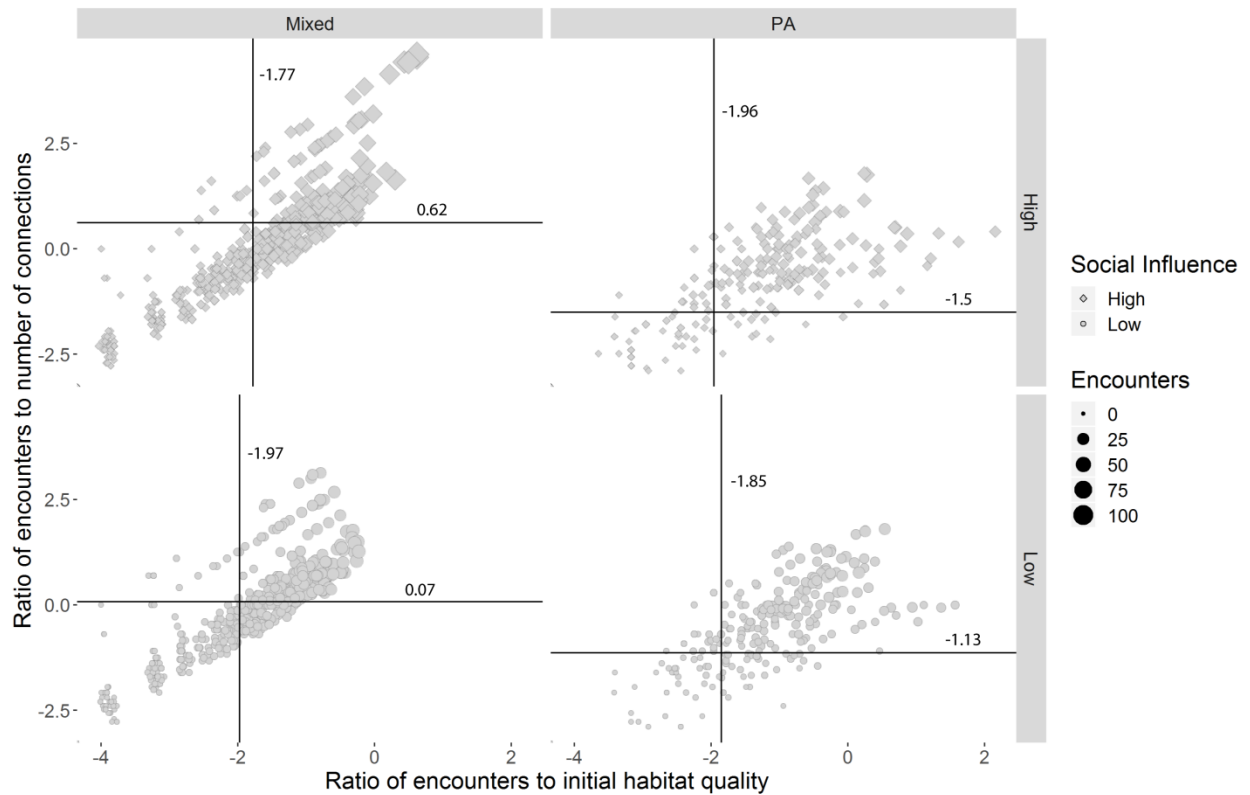


Figure 5: Relative number of total encounters (dot size) over the entire simulation for every farmer relative to the initial habitat quality on the farm and number of connections in the farmer's social network (log scale on y- and x-axes). Simulations were run with high (diamond) and low (circle) social influence and for both mixed and protected-area landscapes (solid lines, log of mean values for each outcome; location of a point on both x- and y-axes represent the degree to which farmers deviate from the means of the entire population of farmers).