Protect Thy Neighbor: Investigating the Spatial Externalities of Community Wildfire Hazard Mitigation

David Butry and Geoffrey Donovan

Abstract: Climate change, increased wildland fuels, and residential development patterns in fire-prone areas all combine to make wildfire risk mitigation an important public policy issue. One approach to wildfire risk mitigation is to encourage homeowners to use fire-resistant building materials and to create defensible spaces around their homes. We develop a theoretical model of interdependent household wildfire risk and mathematically introduce two new concepts of the benefits accruing from hazard mitigation: direct and spillover (indirect) damage averted. We explore how firewise communities can best spend and position mitigation resources to maximize the sum of direct and spillover damage averted. Simulating wildfire behavior within a fire-prone community, our results indicate that homeowners' wildfire risk reduction actions can have significant, positive spillover effects on the wildfire risk of neighboring houses. In such cases, individual homeowners may engage in inefficient levels of wildfire risk mitigation when viewed from the community perspective. We use a simulation approach to demonstrate that wildfire risk reduction is most effective when concentrated in houses at the interface of communities and wildlands. FOR. SCI. 54(4):417–428.

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In the last 20 years, the average annual area burned by wildfire has increased in much of the western United States (Westerling et al. 2006). This increase has been attributed to two main factors: drought conditions in much of the western United States and increasing hazardous fuel [1] loads resulting from a century of wildfire suppression (Calkin et al. 2005). The last two decades have also seen an increase in housing development in fire-prone areas. The wildland–urban interface (WUI), where houses abut or intermingle with forested lands, grew 19.2% in the 1990s to cover 9.4% of the contiguous United States (Stewart et al. 2005). More importantly, the WUI now includes 38.5% of all houses in the country, up 22.3% from 1990 levels (Stewart et al. 2005).

In 2000, the National Fire Plan was established to ensure that firefighting resources are able to respond to wildfires that threaten values at risk (people and property), reduce dangerous fuel loads on the nation's forests and wildlands, and provide assistance to communities threatened or affected by wildland fire hazards (National Fire Plan 2007). Communities have also responded to the growing wildfire problem by educating homeowners and creating public outreach programs; assessing the risk of localized wildfire; providing homeowner assistance, including help in creating defensible spaces; and implementing regulations (Reams et al. 2005). Consequently, reducing the threat that wildfire poses to houses has become an important public policy issue; however, quantifying this risk remains a daunting challenge (Finney 2005).

Policies intended to reduce wildfire hazard in and around WUI communities fall into two main categories. First are policies that encourage the modification of forest structure and fuels, so that wildfires that do occur are easier to control and pose a diminished threat to houses. In addition to the National Fire Plan, the 2003 Healthy Forests Restoration Act streamlined the planning requirements for fuel reduction treatments on federal land (White House 2003). Second are policies that encourage homeowners to make their houses more fire resistant or zoning restrictions that affect land-use decisions. For example, the Firewise Communities Program (2008) provides information on how to make houses less susceptible to wildfire. Other programs offer financial incentives to homeowners to encourage risk reduction by, for example, replacing wood roofs with more fire-resistant materials and removing flammable vegetation (Talberth et al. 2006).

Currently, Firewise recognizes over 300 communities across the United States that are actively engaged in wildfire-risk mitigation activities. Although these mitigation actions may reduce risk and Firewise touts a great many success stories, there is little, if any, empirical evidence of their cost-effectiveness. This lack of analysis is due, in large part, to the difficulty of estimating the benefits of mitigation. Much of the benefit estimation research has focused on perceived benefits (e.g., Winter and Fried 2001, Fried et al. 1999).

Benefit estimation is particularly complex, as homeowners' mitigation actions can have spillover effects on the wildfire risk of neighboring houses (Cohen 1994, 2000, Rehm et al. 2003, Brenkert-Smith et al. 2006, Rehm 2006). This is because houses typically contain much denser fuel than surrounding wildlands (Rehm et al. 2003), and, therefore, mitigation actions that decrease the probability of a house igniting also decrease the probability that neighboring houses will burn.

Failure to account for the positive spillover effects of

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mitigation can lead to inefficient levels of hazard mitigation investment. Indeed, if spillover benefits are substantial, it may be inefficient for all homeowners to participate in mitigation activities. A similar situation occurs in public health: vaccinating a proportion of the population against infectious disease has beneficial spillover effects for the unvaccinated population, because vaccinated individuals cannot contract or spread the infection, which limits the disease exposure for the nonvaccinated individuals. In turn, this can create an interesting condition, known as "herd-immunity," such that only a proportion of the vulnerable population needs to be treated to provide a level of protection to the full population (Anderson and May 1985, 1990, Fine 1993). Ignoring these spillover benefits has been shown to undervalue the cost-effectiveness of vaccination programs (Brisson and Edmunds 2003). In addition, greater voluntary participation in vaccination programs occurs when patients recognize that their participation can benefit others through these secondary (spillover) effects (Hershey et al. 1994).

Indeed, threshold effects, similar to the concept of herd-immunity, are supported by percolation theory, which examines connectivity (Frisch and Hammersley 1963, Shante and Kirkpatrick 1971). In their study of plant pathology, Otten et al. (2004) found that removing 60% or more of the sites limited fungal spread. In Loehle's (2004) study of fire spread as a percolation process, treating 30% of wildland fuels produced a fireproof landscape (i.e., a landscape with limited percolation).

Several studies have examined the spillover effects of wildfire risk reduction. Finney (2001) examined how the spatial arrangement of fuel treatments attenuates wildfire behavior. Loehle (2004) found that nonrandom patterns of fuels treatment allowed significantly less burning in adjacent lands than did random patterns. Shafran and Flores [2] used game theory to study the mitigation choices of homeowners. Brenkert-Smith et al. (2006) found that homeowners' mitigation decision processes are complex with a strong social component and are dependent on the mitigation decisions of other homeowners. Menz et al. (1999) considered the spillover effects fire risk has on farming decisions in Indonesia and examined the benefits from community mitigation action. Although many studies find evidence of spillover effects, we could find no studies that have attempted to quantify the spillover effect of wildfire mitigation actions in the WUI.

The goal of this study is twofold. First, we present a theoretical model for identifying the direct and spillover benefits of homeowners' mitigation actions. Second, we use a stochastic simulation to examine factors that influence the relative size of spillover benefits. The rest of the article is structured as follows: we present a theoretical model of homeowners' wildfire-risk mitigation decisions; we develop a stochastic simulation model of wildfire risk mitigation and apply it to a hypothetical community; and we discuss the results of the theoretical and empirical models and offer recommendations.

Theory

To better understand how wildfire spreads in the WUI, we decompose the fire contagion process into two components: attack and ignition. A burning house [3] (or area of wildland) can attack adjacent houses and wildland through direct flame contact, radiant heat, or embers (firebrands). Therefore, holding weather constant, the probability that a house or area of wildland is attacked by wildfire is a function of its surroundings. In contrast, the probability that this attack leads to ignition depends on the flammability of the house or wildland but not its surroundings. This decomposition of the fire contagion process is similar to infectious disease transmission. Infectious disease transmission has two components: exposure and infection. The probability that an individual is exposed to a disease is a function of contact with infected people (or other vectors of disease), whereas the probability that exposure leads to infection is a function of the individual's disease susceptibility (or immune system).

We are interested in the effect homeowner mitigation has on the spatial distribution of fire risk in the WUI. We examine two steady states (states of nature): the unmitigated community (status quo) and the mitigated community (a firewise community). In the mitigated community, some, but not necessarily all, of the houses are mitigated against wildfire; that is, some homeowners have taken steps to reduce the probability their house will ignite during a WUI fire event. We assume the level of public and private firefighting to be independent of the mitigation state.

In the unmitigated steady-state, the probability that an individual house i burns, B_i^u, is a function of its ignition probability, R_i^u, and the number of times it is attacked by fire, A_i^u:

$$B_i^u = 1 - (1 - R_i^u)^{A_i^u}. \tag{1a}$$

In the mitigated steady state, the probability that an individual house i burns, B_i^m, is a function of its ignition probability, R_i^m, and the number of times it is attacked by fire, A_i^m:

$$B_i^m = 1 - (1 - R_i^m)^{A_i^m}. \tag{1b}$$

The number of attacks a house experiences is a function of the neighboring houses' ignition risk and a portmanteau variable (W) that includes all other relevant physical characteristics of the study area and weather,

$$A_i^u = f_A(R_1^u, R_2^u, \ldots, R_n^u, W) \quad A_i^m = f_A(R_1^m, R_2^m, \ldots, R_n^m, W), \tag{2a}$$

where

$$\frac{\partial A_i^u}{\partial R_i^u} = \frac{\partial A_i^m}{\partial R_i^m} = 0. \tag{2b}$$

Examination of Equations 1 and 2 shows that the probability of a house burning is a function of the ignition risk of all houses including its own, but the probability that a house is attacked by fire is a function of other houses' ignition risks but not its own. Homeowners can only affect their own house's burn probability through changes to their house's ignition probability (i.e., through changes to building materials or landscaping (see [3], although their effect on ignition risk need not be equal); only the actions of neighboring homeowners can affect the probability that a house is attacked by fire. House ignition probability, mitigated or unmitigated, is a function of building materials and construction design (M), landscaping (L), and W and is independent of other houses,

$$R_i^u = f_R(M_i^u, L_i^u, W) \quad R_i^m = f_R(M_i^m, L_i^m, W). \tag{3}$$

The total damage averted from wildfire due to mitigation actions on a group of n houses [4] is the difference between the amount of damage that would occur in the presence and absence of mitigation and may be expressed as

$$T = \sum_{i=1}^{n} V_i(B_i^u - B_i^m), \tag{4}$$

where V_i is the market value of house i. Substituting 1 into 4 yields

$$T = \sum_{i=1}^{n} V_i\{(1 - R_i^m)^{A_i^m} - (1 - R_i^u)^{A_i^u}\}. \tag{5}$$

Spillover and Direct Effects of Mitigation Actions

The total damage averted due to mitigation can be decomposed into two effects: direct damage averted and spillover (indirect) damage averted. Direct damage averted is the value of damage avoided that accrues to the mitigating homeowner. If neighboring houses also experience an attenuation of fire risk from the actions of the mitigating homeowner, the benefit to the neighboring homeowners is the spillover (indirect) damage averted.

Although the idea of direct and spillover damage averted is rather intuitive, they have not, as yet, been represented in a rigorous, mathematical manner. The key to doing so is to recognize that the direct damage averted due to mitigation is manifest through a reduction the ignition risk of a house with the number of attacks a house experiences held constant, because changes in the number of attacks a house experiences are due to changes in the ignition risk of other houses,

$$D = \sum_{i=1}^{n} V_i\{(1 - R_i^m)^{A_i^u} - (1 - R_i^u)^{A_i^u}\}. \tag{6}$$

This follows because an individual homeowner can only affect his or her own ignition risk (e.g., building materials and landscaping) but not risk exposure. Similarly, inoculation reduces a treated individual's probability of infection but not exposure to the disease.

The spillover damage averted due to mitigation is manifest through a reduction in the number of times a house is attacked with the ignition risk of a house held constant [5],

$$S = \sum_{i=1}^{n} V_i\{(1 - R_i^m)^{A_i^m} - (1 - R_i^m)^{A_i^u}\}. \tag{7}$$

This follows because the action of others reduces the individual homeowner's risk exposure but not probability of ignition. Similarly, inoculation of others reduces an untreated individual's probability of exposure, but not his or her capacity to ward off infection.

The value of the direct and spillover damage averted is then a function of ignition risk and attack (exposure) risk, both before and after mitigation, and the dollar value of an unit of damage averted from wildfire.

Optimal Community Mitigation

If homeowner wildfire risk is interdependent, then collective action is needed to achieve optimal community levels of mitigation. Determination of the optimal level and spatial arrangement of mitigation for a community can be expressed as a profit maximization problem (maximizing the difference between total damage averted [Equation 5] and mitigation costs):

$$\max_{R_1^m,\ldots,R_n^m} \pi = \sum_{i=1}^{n} V_i\{(1 - R_i^m)^{A_i^m} - (1 - R_i^u)^{A_i^u}\} - C_i(R_i^u - R_i^m), \tag{8}$$

where C_i denotes the constant per-unit cost of mitigation for the ith house.

Differentiating with respect to R_i^m yields the following n first-order conditions:

$$\frac{\partial \pi}{\partial R_i^m} = -V_i A_i^m (1 - R_i^m)^{A_i^m - 1} + \sum_{\substack{j=1,\\ j \neq i}}^{n} \left(V_j (1 - R_j^m) A_j^m \ln(1 - R_j^m) \frac{\partial A_j^m}{\partial R_i^m} \right) + C_i = 0. \tag{9}$$

Rearranging 9 yields an expression for the optimal ignition risk R_i^{m*} for each house,

$$R_i^{m*} = 1 - \left(\frac{\sum_{\substack{j=1,\\ j \neq i}}^{n} V_j \left\{ (1 - R_j^m)^{A_j^m} \ln(1 - R_j^m) \frac{\partial A_j^m}{\partial R_i^m} \right\} + C_i}{V_i A_i^m} \right)^{1/(A_i^m - 1)}. \tag{10}$$

Equation 10 shows that, when considering the community as a whole, the optimal level of ignition risk for one house depends on the ignition risk of other houses in the community and their spatial arrangement, because the spatial arrangement of houses can affect $\partial A_j^m / \partial R_i^m$.

For the community, the optimal level of mitigation investment is

$$I^* = \sum_{i=1}^{n} C_i \left\{ R_i^u - 1 + \left(\frac{\sum_{\substack{j=1,\\ j\neq i}}^{n} V_j \left\{ (1 - R_j^m)^{A_j^m} \ln(1 - R_j^m) \frac{\partial A_j^m}{\partial R_i^m} \right\} + C_i}{V_i A_i^m} \right)^{1/(A_i^m - 1)} \right\}. \tag{11}$$

Optimal Homeowner Mitigation

If homeowner wildfire risk is interdependent, but not quantifiable, homeowner investment decisions will diverge from the optimal community investment level. Determining the optimal level and spatial arrangement of mitigation at the individual homeowner level may also be expressed as a profit maximization problem. However, in this case, the homeowner only considers the direct damages averted by mitigation (Equation 6) and mitigation costs,

$$\underset{R_i^m}{\text{MAX}}\ \pi_i = V_i\{(1 - R_i^m)^{A_i^u} - (1 - R_i^u)^{A_i^u}\} - C_i(R_i^u - R_i^m), \tag{12}$$

The n first order conditions are

$$\frac{\partial \pi_i}{\partial R_i^m} = -V_i A_i^u (1 - R_i^m)^{A_i^u - 1} + C_i = 0. \tag{13}$$

Rearranging 13 yields an expression for the optimal ignition risk for each house considering only the direct effects of mitigation ($\tilde{R}_i^{m*}$),

$$\tilde{R}_i^{m*} = 1 - \left(\frac{C_i}{V_i A_i^u} \right)^{1/(A_i^u - 1)}. \tag{14}$$

Unlike the community solution, the myopic homeowner solution is aspatial, because it is independent of all other houses in the community. The communitywide level of investment is

$$\tilde{I}^* = \sum_{i=1}^{n} C_i \left\{ R_i^u - 1 + \left(\frac{C_i}{V_i A_i^u} \right)^{1/(A_i^u - 1)} \right\}. \tag{15}$$

Divergence of the Optimal Community and Homeowner Solutions

The individual and the community solutions coincide when the number of attacks a house experiences is independent of the ignition risk of all other houses ($\partial A_j^m / \partial R_i^m$, for all i) [6]. If this condition does not hold, then the optimal community and homeowner solutions may diverge. Examination of 10 and 14 does not indicate, a priori, the direction and magnitude of this divergence. Thus, we cannot determine whether the individual level of investment is biased upward or downward of the optimal community level of investment, but we can gain some useful insights into how the direction of dependence biases the individual solution.

Suppose there are two groups of houses, g and k, where group g is downwind of group k. Therefore, the ignition risks of houses in group g do not affect the fire attack probabilities of houses in group k ($\partial A_k^m / \partial R_g^m = 0$), but the ignition risks of houses in group k do affect the fire attack probabilities of houses in group g ($\partial A_g^m / \partial R_k^m > 0$). For simplicity, we further assume that the fire attack probabilities of houses in each group are independent of the ignition risk of other houses in the same group. This wind-based asymmetry causes the community and homeowner solutions to diverge in different ways. The community solution for group k is

$$R_k^{m*} = 1 - \left(\frac{\sum_{g=1}^{G} \left(V_g (1 - R_g^m)^{A_g^m} \ln(1 - R_g^m) \frac{\partial A_g^m}{\partial R_k^m} \right) + C_k}{V_k A_k^m} \right)^{1/(A_k^m - 1)} < \tilde{R}_k^{m*} = 1 - \left(\frac{C_k}{V_k A_k^u} \right)^{1/(A_k^u - 1)}, \tag{16}$$

where $A_k^u = A_k^m$ because $\partial A_k^m / \partial R_g^m = 0$ (and k-group houses are independent of other k-group houses). The community solution for group g is

$$R_g^{m*} = 1 - \left(\frac{C_g}{V_g A_g^m} \right)^{1/(A_g^m - 1)} > \tilde{R}_g^{m*} = 1 - \left(\frac{C_g}{V_g A_g^u} \right)^{1/(A_g^u - 1)}, \tag{17}$$

because $A_g^u > A_g^m$ [7]. Compared with the community optimum, the k-group houses would underinvest in mitigation, and g-group houses would overinvest in mitigation if the groups act individually. Group k houses underinvest because they do not consider the spillover effects of their mitigation decisions on g-group houses; g-group houses overinvest because they do not consider the spillover effects of k-group houses on their own fire attack probabilities. This example demonstrates that failing to internalize the spillover damage averted from wildfire by mitigation can lead to suboptimal investment decisions with complex, spatially distributed implications.

The optimal level of ignition risk (Equation 10) or (Equation 14) cannot be solved explicitly unless the functional relationship between the number of attacks a house experiences, ignition risk, and weather is known for all houses (Equations 2a and 2b). Unfortunately, the literature provides little guidance on an appropriate functional form, and even if we assume one, any but the simplest would be unlikely to yield a closed-form solution. For this reason, we develop a stochastic model of fire behavior to evaluate the consequences of household wildfire risk mitigation actions.

Simulation Method

As in the Theory section, we are interested in the effect homeowner mitigation has on the spatial distribution of fire risk in the WUI. However, now we create the fire attack process using a stochastic fire-spread model. Again, we examine two steady states: the unmitigated community and the mitigated community (where some of the houses are mitigated against wildfire).

Fire-Spread Model

The modeling architecture we use is similar to the cellular automaton approach first developed by Von Neumann (1966) and subsequently refined by several authors (Clarke et al. 1994, Karafyllidis and Thanailakis 1997, Hargrove et al. 2000, Berjak and Hearne 2002). Cellular automaton models divide a landscape into a regular grid pattern. The cells of the grid can have two states and the cells' state is governed by a set of rules. In the case of fire spread, a set of rules dictate the spread of fire from cell to cell. Cells, then, can take on one of two states: unburned or burned. After an initial ignition, the model determines, using a percolation process (the rules), whether the fire spreads from burned cells to adjacent unburned cells based on user input spread probabilities. The spread probabilities and how they influence the state of each cell constitute the rules. For instance, if the probability of spread from a burned cell to an adjacent unburned cell is greater than or equal to a random number drawn from an uniform probability distribution, then the unburned cell changes state and becomes burned. The model then evaluates whether fire spreads from this newly burned cell to other adjacent unburned cells and so on. Cellular (cell-to-cell) fire spread continues until all available cells have burned or the fire fails to spread (the unburned cells fail to ignite). Recent refinements include the effect of wind (Hargrove et al. 2000) and allowing cells to burn for more than one time step (Favier 2004).

Although our model is based on a cellular approach, it has several key differences. The most important is that we treat houses as points on a landscape not cells. The fire-transfer mechanism is based on the distance between houses (points) and is not restricted to boundary-sharing cells, as in conventional cellular automaton models. We use this modeling approach because the developed landscapes we are modeling exhibit greater variation in fuel levels over shorter distances than do wildlands. In particular, fuels are concentrated in houses, which, even in a dense housing development, occupy a small portion of the landscape. Therefore, we decided to represent houses as discrete points on a landscape and not as homogeneous cells. In contrast, wildland fuels are more continuous and so are more readily represented as homogeneous cells.

Simulation Design

Our simulated WUI landscape is populated with 400 houses following a regular 20 by 20 pattern. (A regular housing pattern was chosen for convenience.) A forest, which abuts the 20 western-most houses, is the source of all wildfire risk. Fire propagation is governed by the ignition probabilities of houses and the number of times they are attacked by fire. Ignition probabilities are predefined, whereas the number of attacks houses experience is determined by the stochastic simulation process.

Currently, validated models predicting fire spread within the WUI do not exist (Evans et al. 2004). There has been some recent work in the area of WUI fire transmissions (e.g., Rehm 2006, Spyratos et al. 2007), but a unified model of community-scale, house-to-house fire spread, which incorporates extreme weather conditions (e.g., hot, arid, and windy weather) that accompany WUI fire events, appears to be lacking. However, observations of wildland fire behavior suggest that any model should obey certain principles. Therefore, we selected a conditional attack function—the fire attack probability for house i, given burning house j—that would satisfy three conditions (all else equal): the probability that a burning house attacks a nonburning house declines as the distance between the two houses increases; the probability that a burning house attacks a nonburning house increases as wind speed increases in the direction of the nonburning house; and nonburning houses downwind of a burning house are more likely to be attacked than those upwind. These criteria are intuitive, and they are also consistent with theoretical models of fire spread, such as the Rothermel (1983) model. The specific fire attack probability chosen is

$$\Pr(A_{ij} = 1 | F_j = 1) = R_j\left(\frac{\delta_0}{\delta_{ij}}\right)^2 \left(1 + \left(\frac{\psi}{\psi_0}\right)\mathrm{Cos}\,\vartheta_{ij}\right), \tag{18}$$

where $A_i = \sum_{j=1, j\neq 1}^{n} A_{ij}$, F_j denotes burning status of j (1 burning; 0 otherwise), δ_0 is a reference distance, δ_{ij} is the distance between house i and j, ψ_0 is a reference wind speed, ψ is the wind speed, and ϑ_{ij} is the angle (in radians) of house j relative to the direction of the wind heading from burning house i. Reference distance and wind speed are used to keep distance and wind speed in dimensionless units.

We chose to represent the effect of distance on attack probability with an inverse distance-squared relationship [8], as we assume that the probability of radiant ignition declines with distance between structures and the change in decline also decreases with distance. Relative wind angle is used to modify the distance-weighted attack probability to account for a target house being upwind or downwind from a burning house. Reference factors are used to normalize distance and wind speed. Windblown fire brands (embers) are believed to be a major source of ignitions. Unfortunately, the literature provides little guidance on the behavior of fire brands, and any plausible model of fire brands would satisfy the three conditions listed above. Therefore, our model is not intended to describe fire behavior quantitatively, but for our purposes, we believe it does represent fire spread in a qualitatively correct manner. However, allowing distance to modify attack probability, so fire spread can occur between nonadjacent houses, qualitatively mimics ember attack.

We did not calibrate the model for any particular set of burning conditions, so the actual units used for distance and wind speed are only related to the reference values (distance and wind speed values are unitless). Instead, to represent an interesting range of burning conditions, we manipulated wind speed so that 50, 75, and 95% of houses in the unmitigated, homogeneous landscape (all houses have the same ignition probability) were destroyed. (Hereafter, we refer to these burning conditions as 50, 75, and 95% weather conditions, respectively.) This approach allowed us to qualitatively investigate and draw general conclusions about the effect of weather severity without the difficulty and uncertainty of calibrating the model to a specific set of burning conditions. The simulation framework also allowed us to examine how direct and spillover mitigation benefits accrue under varying scenarios. To answer quantitative questions about a particular site—do the benefits of a particular mitigation strategy outweigh the costs?—would require a quantitatively correct model of wildfire spread through the WUI. This would necessitate a substantial advance in fire modeling and is beyond the scope of this article.

The fire-spread process is composed of two parts: attack and ignition (Figure 1). The simulation begins with an attack of the first 20 western-most houses and continues iteratively until additional houses fail to ignite or all 400 houses in the community are destroyed [9]. Note that each simulation represents a single fire event, but the aggregate of all simulations is not meant to represent a fire season or other length of time. Rather the simulations represent the variability of a single fire event.

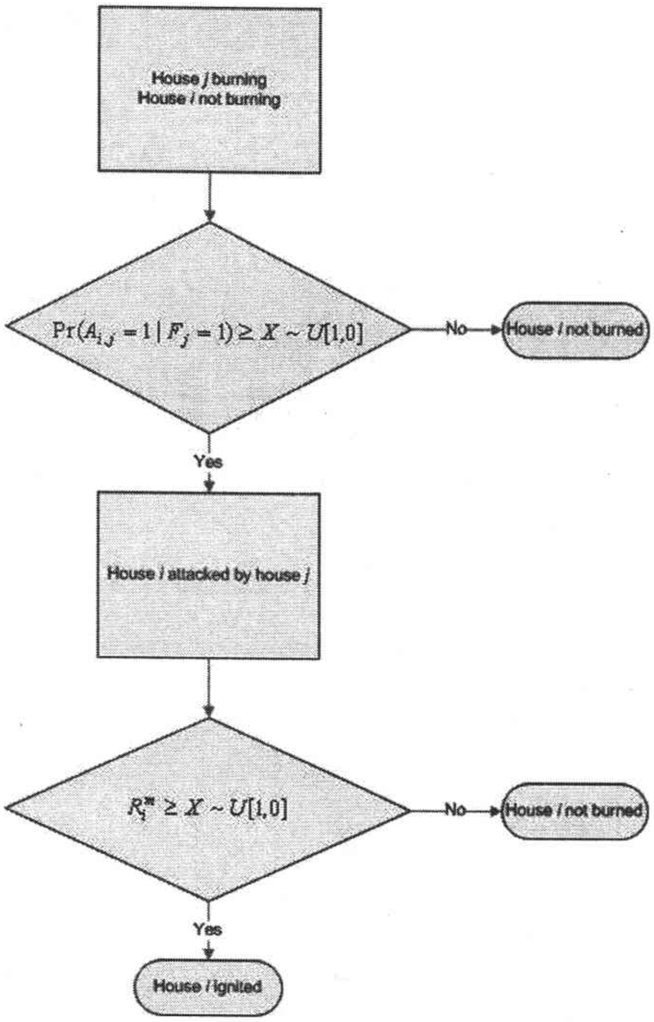

Figure 1. Flow chart describing the simulation's fire attack and ignition process between two houses (*i* and *j*).

Mitigation Strategies

We evaluate the effects of six mitigation strategies (three risk-based and three spatially based) have on the fire-spread process (Table 1). The risk-based mitigation strategies differ in their prioritization of targeting high, medium, or low fire ignition probability houses. The spatially based mitigation strategies (Figure 2) select houses depending on their location within the community and relative distance to the wildland hazard. A buffer mitigation pattern was shown to be effective in controlling the spread of pests (Sharov and Liebhold 1998a, 1998b); a herringbone fuels management pattern was shown to be effective in controlling the spread of fire in wildlands (Finney 2001); the random mitigation pattern is used as a control.

We analyzed the effects of wildfire risk mitigation using either a heterogeneous or a homogeneous ignition-risk landscape. In the heterogeneous landscape, the ignition probabilities [10] were drawn randomly from a uniform distribution with an interval of 0.2–0.4 and a mean of 0.3 ($R^u \sim U[0.2, 0.4]$. In the homogeneous landscape, the ignition probabilities were set to 0.3 ($R_i^u = 0.3$). In addition, we set the value of all houses to \$100,000 (V_i = \$100,000). We then incrementally mitigated the landscape using either one of three spatially based mitigation strategies (buffer, herringbone, and random) (Figure 2) or one of three ignition risk-based mitigation strategies. (The risk-based mitigation strategies could only be evaluated using the heterogeneous landscape.) Each increment of mitigation reduces the ignition risk of 20 houses by 0.1. (After 20 increments of mitigation, all 400 houses were mitigated.) After each increment of mitigation, we burned the landscape and calculated the direct damage averted and spillover damage averted by mitigation using the unmitigated landscape as a baseline. For each increment of mitigation we conducted 5,000 simulations [11]. Evaluating one mitigation strategy required 105,000 simulations: 20 increments of mitigation and a no-mitigation baseline. Each of the six mitigation strategies were evaluated under 50, 75, and 95% weather conditions.

Table 1. Combination of mitigation strategies, weather, ignition risks, and mitigation intensities used in the wildfire simulations (72 combinations)

Mitigation strategies
Buffer
Herringbone
Random
High-risk houses first
Low-risk houses first
Medium-risk houses first
Weather
50% of unmitigated landscape burns
75% of unmitigated landscape burns
95% of unmitigated landscape burns
Ignition risk
Homogeneous (0.3)
Heterogeneous (0.2–0.4)
Mitigation intensity
Ignition risk reduced by 0.1
Ignition risk reduced by 0.2

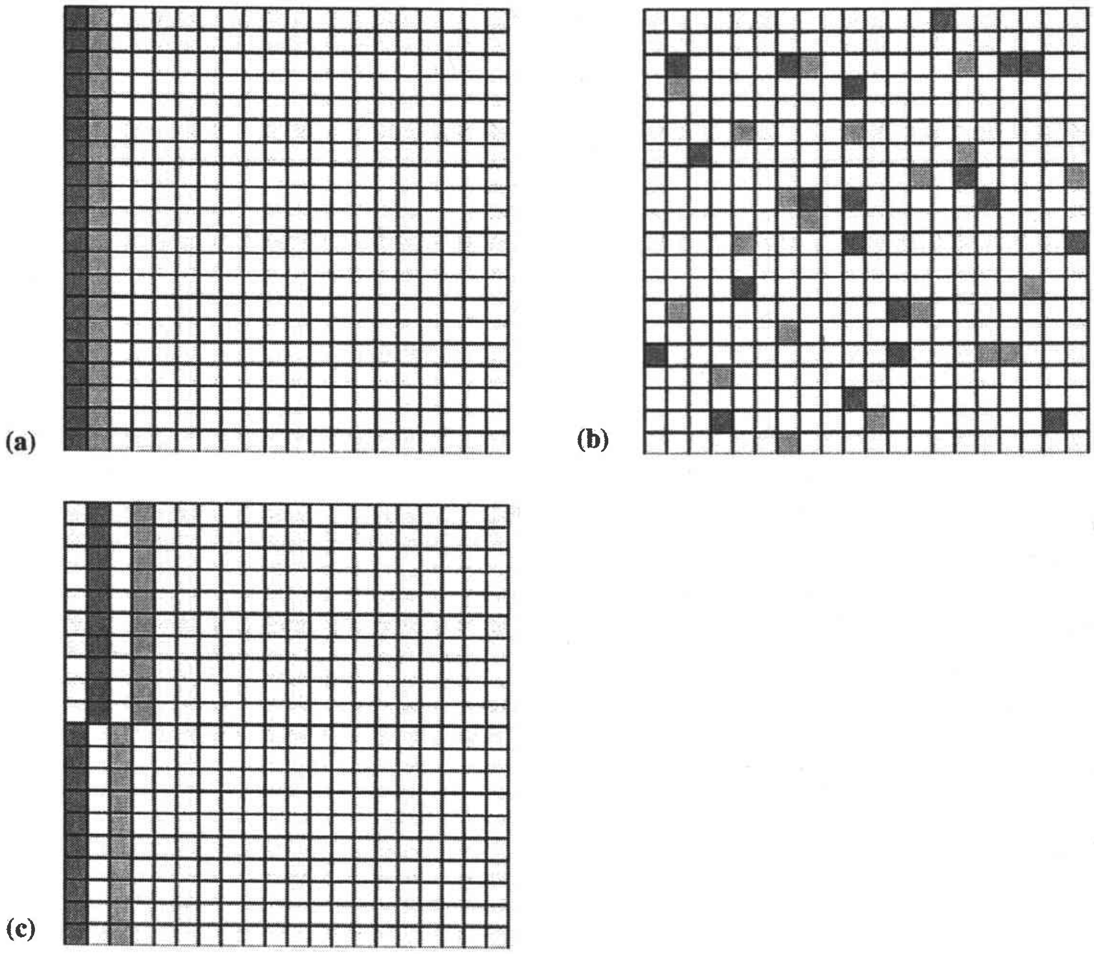

Figure 2. (a) Buffer mitigation strategy. The area in dark gray denotes the first increment of 20 mitigated houses. The area in light gray denotes the second increment of 20 mitigated houses. Mitigation follows this pattern, until after 20 increments all 400 houses are mitigated. (b) Random mitigation strategy. (c) Herringbone mitigation strategy (This mitigation strategy was designed to roughly mimic the pattern that Finney [2001] showed to be effective at altering wildfire behavior in wildland fuels.) After 10 increments of mitigation (200 houses), the herringbone pattern covers the entire grid. Further increments of mitigation fill in the areas left blank. Therefore, for increments 11 through 20 the herringbone pattern is a hybrid of the buffer and herringbone strategy.

To examine the effect of mitigation intensity, we reevaluated all six mitigation strategies with mitigation increments of only 10 houses, but the ignition risk of each house was reduced by 0.2 as opposed to 0.1. All of the above mitigation permutations are summarized in Table 1. Simulations were coded in Visual Basic for Applications.

Results

We ran all 72 scenarios summarized in Table 1. However, because of space limitations, we first focus on the results from the heterogeneous landscape with low-intensity mitigation and then note any substantive differences from this base case. Figure 3a–c presents the direct and spillover effects of the three spatially based mitigation strategies with heterogeneous ignition risk and mitigation increments of 0.1 under 50, 75, and 95% weather, respectively (switching to a homogeneous ignition risk had little effect on results). Figure 3d presents the total damage averted (direct effect plus spillover effect) from mitigation under 50 and 95% weather. (Results for 75% weather are excluded for clarity; they fall between those for 50 and 95% weather.) The buffer mitigation strategy results in more total and spillover damage averted than the other two spatially based strategies [12]. For example, the first increment of buffer mitigation averts more than four times the damage of the first increment of random mitigation. The sensitivity of the spillover effect to the spatial arrangement of mitigation has policy implications. For example, if homeowners are offered subsidies to mitigate the fire risk of their houses, then those administering the subsidy program should consider offering differential subsidies depending on the location of a house. In contrast to spillover, the direct damages averted by mitigation are approximately linear and insensitive to the spatial arrangement of mitigation.

Figure 3 also shows how weather severity affects mitigation efficacy. For example, the direct damage averted by buffer mitigation [13] increases with weather severity. This is not surprising, as more severe weather increases the number of unmitigated attacks a house experiences, and Equation 6 shows that increasing the number of unmitigated attacks increases the direct effect of mitigation (assuming

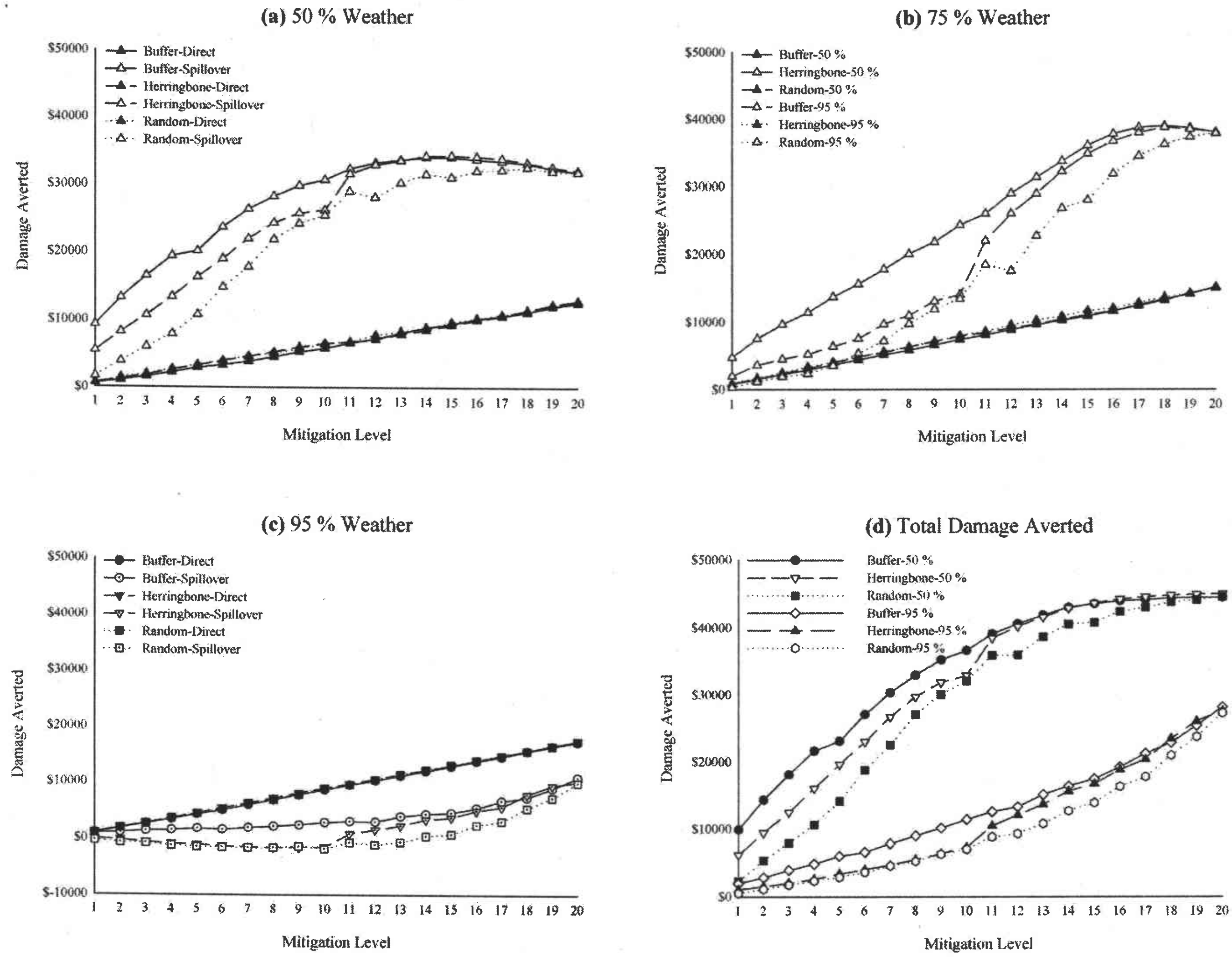

Figure 3. The direct and spillover effects of the buffer, herringbone, and random mitigation strategies with heterogeneous ignition risk and mitigation increments of 0.1 under (a) 50% weather, (b) 75% weather, (c) 95% weather, and (d) total damages averted (direct effect + spillover effect) under 50 and 95% weather.

$R_i^m < R_i^u$). The effect of weather on spillover is more complex. With fewer mitigated houses, severe weather results in lower spillover effects. This result, coupled with Equation 7, implies that the difference between the number of attacks in an unmitigated and a mitigated landscape is smaller with more severe weather, at least when the number of mitigated houses is small. Note that the spillover effects-to-mitigation–level relationship is convex under 95% weather and concave under 50% weather. This implies that the returns to mitigation are increasing and decreasing, respectively.

Spillover damages averted are sometimes negative with severe weather (Figure 3c), which implies that mitigation increases the number of attacks in the community. Mathematically, a negative spillover exists when $(1 - R_i^m)^{A_i^m} < (1 - R_i^m)A_i^u$ [14]; however, an intuitive reason also exists. Imagine a fire line advancing into a mitigated area. Mitigation causes discontinuity in the fire line, as houses are able to successfully repel the fire owing to their decreased ignition risk, thus creating a jagged and deeper fire line. While the fire line continues to advance on the unmitigated areas, as is probably the case during times of extreme fire weather, the jagged "fingers" of the fire line work themselves around the mitigated houses, now attacking the mitigated structures from multiple angles. This occurrence then increases the number of attacks in a mitigated landscape during times of extreme fire weather, because in the unmitigated landscape, fires are more successful at igniting houses with fewer attacks. In a study of WUI fire spread, burning houses were found to entrain the fire line, slowing down its advance, thus increasing the exposure time nonburning structures experience (Rehm 2006). However, as might be expected, even when negative spillover effects occur, they are dominated by the direct effect of mitigation: in all cases the total effect of mitigation is positive.

The sensitivity of spillover to weather conditions has important policy implications. For example, if homeowners are offered subsidies to mitigate the fire risk of their houses, then those administering the subsidy program should consider the severity of fires that are likely to occur. If an area is prone to severe fires, then the spillover effects of homeowners' mitigation actions may be small. Under such circumstances only modest subsidies would be warranted.

Figure 4a–d shows results for the three risk-based mitigation strategies. In contrast to the three spatially based mitigation strategies, the direct damages averted by the three risk-based mitigation strategies are not the same: targeting the low ignition-risk houses first has the highest direct damages averted and targeting the high ignition-risk houses first has the lowest direct damages averted. This may appear counterintuitive, but consider that a 0.1 reduction in ignition risk for a low ignition-risk house represents a larger percentage decline than for a high ignition-risk house. The spillover damages averted by the three risk-based mitigation strategies, in contrast, exhibit the opposite pattern: targeting the high ignition-risk houses first strategy has the highest spillover damages averted, and targeting the low ignition-risk houses first has the lowest spillover damages averted. Because under 50% weather, spillover effects are much higher than direct damages averted, targeting the high ignition-risk houses first has the highest total damages averted, and targeting the low ignition-risk houses first has the lowest total damages averted (Figure 4a). This result, however, is reversed under 95% weather, because spillover damages averted decline with more severe weather (Figure 4c). The results do not, therefore, provide unconditional guidance on the optimal risk-based strategy—they are weather dependent. However, identifying the optimal risk-based mitigation strategy is to some extent moot, as a comparison of Figures 3 and 4 shows that the buffer and herringbone mitigation strategies outperform all three risk-based mitigation strategies, particularly at low levels of mitigation. This suggests that a spatially based approach to risk mitigation is better than a risk-based approach. Recall that a herringbone pattern is the most effective at reducing severity and slowing fire spread in purely wildland settings (Finney 2001), whereas a buffer pattern is effective in controlling the spread of pests (Sharov and Liebhold 1998a, 1998b).

The simulations described so far involved incrementally mitigating groups of 20 houses by 0.1. To examine the sensitivity of results to mitigation intensity, we repeated all simulations incrementally mitigating groups of 10 houses by 0.2. For the three spatially based mitigation strategies, high-intensity spillover damages averted exceeded low-intensity spillover effects, particularly under 95% weather. Furthermore, the efficacy of high-intensity mitigation is less sensitive to weather

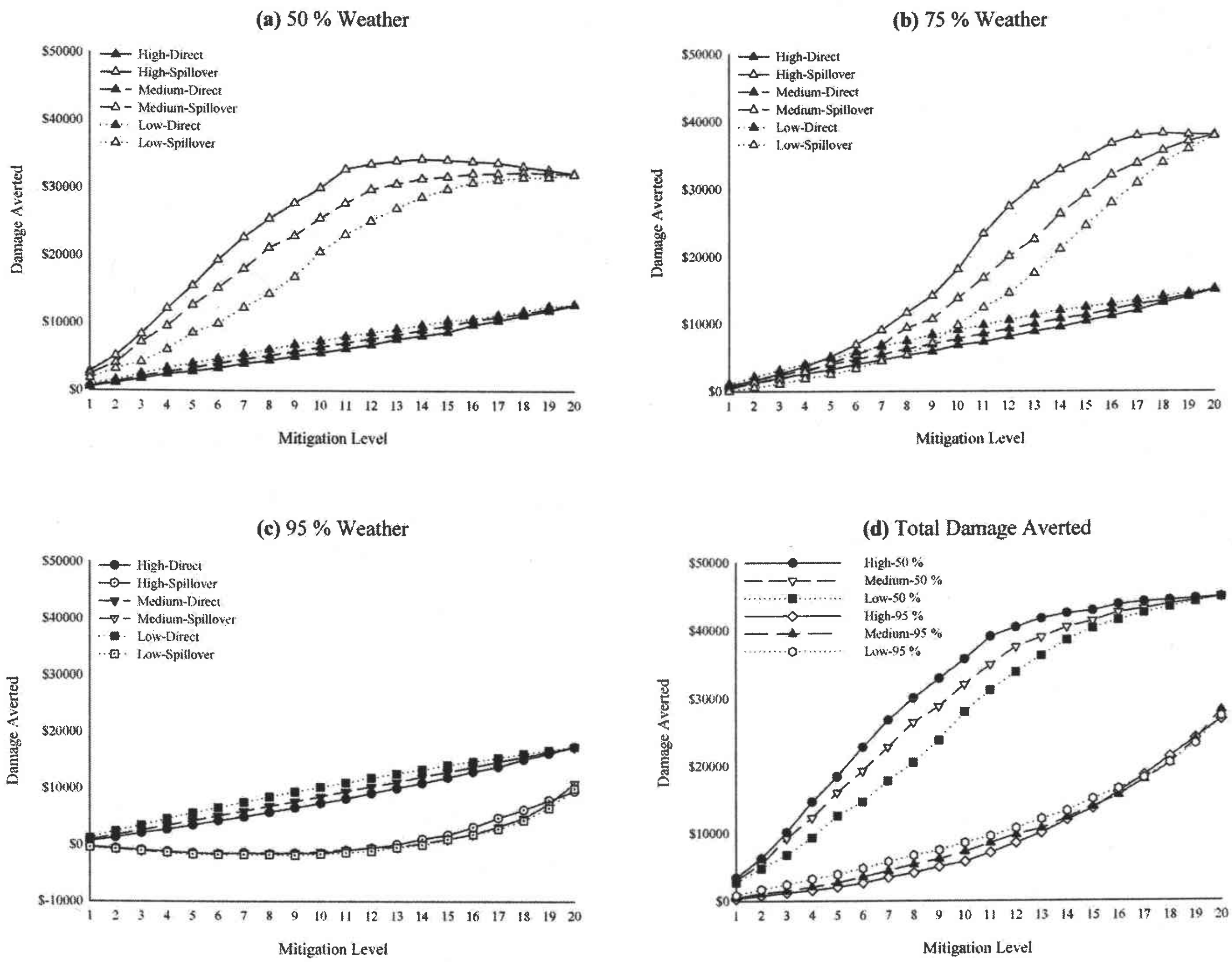

Figure 4. The direct and spillover effects of the high-risk first, medium-risk first, and low-risk first mitigation strategies with heterogeneous ignition risk and mitigation increments of 0.1 under (a) 50% weather, (b) 75% weather, (c) 95% weather, and (d) total damages averted (direct effect + spillover effect) under 50 and 95% weather.

severity. From a policy perspective, this suggests that mitigation is most effective when concentrated on fewer homes.

Cost Considerations

Our empirical model focuses solely on the benefits of mitigation. Mitigation cost information is required to determine the optimal level and spatial placement of mitigation. To compare the costs and benefits of mitigation would require advances in fire modeling because our results are only qualitatively correct and, therefore, comparing the costs and benefits of mitigation would not be meaningful. If quantitatively correct models were developed, they could be coupled with the theoretical, economic model developed here and would provide a powerful tool for decisionmakers in WUI communities, because, in practice, policymakers would need to trade off the costs and benefits of mitigation.

Considering costs could modify some of our findings. For example, we implicitly assumed that the per-unit cost of mitigation is constant: the cost of reducing the ignition risk of one house by 0.2 is the same as reducing the ignition risk of two houses by 0.1, for example. However, homeowners will probably take the lowest cost mitigation actions first (all else being equal), and, therefore, the per-unit cost of reducing ignition may increase with treatment intensity.

Discussion

We presented a theoretical model of wildfire risk mitigation, which explicitly accounts for the spatial interdependence of wildfire risk in WUI communities. The model advances wildfire economic theory by mathematically decomposing the damage averted by mitigation into direct and spillover effects. In addition, our theoretical model allowed us to develop a stochastic simulation model that led to several policy-relevant conclusions about the benefits of wildfire risk mitigation strategies. We report four important findings: (1) if mitigation decisions affect neighboring households, then economic efficiency requires collection action; (2) spatially based mitigation strategies perform better than ignition risk-based strategies; (3) the buffer strategy outperformed all other spatial or risk-based strategies; and (4) spatially concentrating mitigation effort is better than spreading it out.

We have shown that the direct damage averted due to mitigation is related to the reduction in the ignition risk of a house while holding the probability of attack (exposure) constant. When changes in mitigation do not affect the fire attack (exposure) risk of others, then direct damage averted is the only source of mitigation benefits (direct damage averted equals total damage averted). Positive spatial externalities result when changes in mitigation affect the fire attack (exposure) risk experienced by others. This spillover effect, the spillover damage averted due to mitigation, is related to the reduction in the number of times a house is attacked, holding the ignition risk of a house constant. When this occurs, then from a community perspective, the total damage averted no longer equals the direct damage averted, and individual homeowners may invest in an inefficient level of mitigation. However, whether individual investment is biased upward or downward depends on how homeowner mitigation affects the fire attack process.

Our treatment of optimal investment into wildfire mitigation, given the spatial interdependence of risk, is generalizable to other types of hazards. For example, the spread of invasive species is a significant problem in many areas. Invasive species often spread across multiple ownerships in a qualitatively similar way to spread of wildfire, albeit somewhat more slowly. If a physical model of invasive species spread could be developed, then the economic framework presented could be used to examine the spillover effects of controlling them.

As with any empirical or simulation model, there is always a concern that results may be an artifact of the modeling architecture and not of the underlying process being modeled. To address this concern, we systematically varied model assumptions regarding the functional form of the fire attack process (by varying the influence fire weather and distance between houses had on the probability of fire spread), the spatial distribution of ignition risk, and the effect of mitigation on ignition risk. Several robust results emerged from this sensitivity analysis. Perhaps the most general is that the homeowners' wildfire risks can be strongly interdependent. Although spillover damages averted varied widely by simulation scenario, depending on assumptions maintained, they were often greater than the direct damages averted of mitigation and sometimes substantially so. Consequently, there can be a divergence between the optimal level of community and homeowner mitigation. Therefore, unless communities act collectively, it is likely that individual homeowners will engage in inefficient levels of mitigation.

Our comparison of spatially based and risk-based mitigation strategies showed spatially based approaches to be consistently more effective. Of the three spatially based approaches evaluated, the buffer approach was the most cost-effective (given equal mitigation costs across mitigation strategies). The poorer performance of the risk-based mitigation strategies (targeting houses based on ignition probability) may be due, at least in part, to the divergence between ignition probability and burn probability. Intuitively, it makes little sense to mitigate houses with high ignition probabilities, but with low probabilities of being attacked by fire; consider the extreme example of a straw house on an island in the middle of a lake. Unfortunately, identifying the houses with the highest burn probabilities is more difficult than identifying the houses with the highest ignition risks, as an understanding of the attack process is required. The buffer strategy is perhaps most effective because it proxies for high-burn probability areas (buffering begins at the interface area where wildland-to-house transmission occurs).

Mitigation effectiveness decreased with weather severity. This was independent of the mitigation strategy used and resulted from the negative relationship exhibited between weather severity and spillover effect. We found that mitigation can have a sizable effect even during the 95% weather scenario. This finding implies that even under extreme conditions mitigation can provide communities with some significant protection. Of course, the amount of protection depends on the ignition and attack probabilities found in the community, but our results suggest that mitigating against 95% weather using the buffer strategy can protect up to 30% of the community's value. Whether this is economical depends on the costs of mitigation. From a policy perspective, one thing to remember is that a community may encounter a range of fires. If a community assumes large spillover effects and prepares collectively, they will be in good shape most of the time. During a catastrophic fire, spillover effects are lower, but as we have shown, the amount of the damage averted can still be significant.

In general, results suggest that mitigation is most effective if it is concentrated and spatially targeted. For instance, the buffer strategy is not only the most effective, but also we found that concentrating mitigation on fewer houses increased its efficacy and decreased its sensitivity to severe weather. This finding suggests that, depending on costs, constructing a firebreak between the community and the wildland might be a highly effective mitigation strategy. Indeed, for many of our simulations it would be more cost-effective for a homeowner in the interior of the community to help pay for buffer mitigation rather than mitigate their own house (again assuming uniform costs). This finding implies that community policymakers who administer programs that offer mitigation subsidies should consider spatially targeting these subsidies. Finally, the economic framework developed here illustrates that firewise communities are more than simply a collection of firewise houses—mitigation actions are more effective when coordinated across communities.

Our simulation model has some significant limitations. Foremost is the fact that we can only draw qualitative conclusions about mitigation efficacy because, although our simulation qualitatively mimics fire behavior, it was not calibrated to particular burning conditions. This was not just an expedient choice on our part. Although there are several fairly well-accepted models of wildland-fire spread, there are no equivalent models of a wildland fire burning into a developed area (Mell et al. 2007). One shortcoming of using a simulated, qualitatively correct-only fire model is that we are unable to compare the costs and benefits of mitigation. To do this would require an advance in physical fire modeling, which is beyond the scope of this article. However, advancements in physical fire science coupled with the economic model presented here can be used in the future to ensure that firewise communities are truly that.

Endnotes

[1] Fuel refers to downed fuel (dead branches, pine needles, etc.), and standing fuel (live and dead trees and shrubs).

[2] A. Shafran and N.E. Flores, Risk externalities and the problem of wildfire risk. Unpublished draft.

[3] We use the term "house" as shorthand for everything on a property. This includes the house itself as well as the yard. We define the house and the yard together as a singular unit because a homeowner can affect the risk on his house and yard through construction materials and creating defensible space. A house (house and yard) is attacked (exposed to fire) if fire spreads from a burning house (or burning yard) to some portion of the neighboring non-burned property.

[4] These mitigation actions may be taken on all or some of the *n* homes.

[5] The expression can also be derived by subtracting the expression for direct effect from the expression for total effect.

[6] Heterogeneous housing prices could also cause a divergence between the community and individual solution. We do not explore this possibility.

[7] Differentiating (Equation 10) or (Equation 14) with respect to attacks shows that optimal home ignition risk (in these cases) decreases in attacks (proof not shown). However, this assumes that house value multiplied by the number of attacks is greater than the per-unit cost of mitigation and that the number of attacks is >1.

[8] We found that model results were qualitatively insensitive to several monotonic transformations of the inverse distance-squared relationship (results not shown).

[9] Favier's (2004) percolation process allows burning cells to threaten their nonburning Von Neumann neighbors (surrounding eight cells) over multiple time steps. For instance, if a burning cell threatens (attacks) its neighbor but fails to burn (ignite) it, it may threaten its neighbor at the next time step unless the burning neighbor becomes burned (burns out). Cells burning over multiple time steps are called persistent. Using our terms, persistence has the implication of simply modifying the attack probabilities. Because we assume each house to be similar in its rate of burn, then all houses have the same level persistence, so it becomes a nonissue. This might change if we were exploring WUI burn patterns within a mixed built environment—commercial and residential buildings. We leave this for future research.

[10] One possible way of estimating ignition risks in practice would be to use an existing wildfire risk rating system. For example, see the National Fire Protection Association (NFPA 1144) Standard for Protection of Life and Property from Wildfire: Wildland Fire Risk and Hazard Severity Assessment Form.

[11] A total of 5,000 simulations were required to achieve stable estimates of damage averted.

[12] After 10 increments of mitigation, the herringbone strategy becomes as effective as the buffer strategy. This is because after 10 increments of mitigation (200 houses), the herringbone pattern covers the entire grid. For further increments of mitigation, we filled in the areas left unmitigated by the herringbone strategy. Therefore, for increments 11 through 20 the herringbone pattern is a hybrid of the buffer and herringbone strategy.

[13] Herringbone and random mitigation exhibit qualitatively similar results.

[14] For an individual house, negative spillover can occur even when $B_i^m < B_i^u$ and $R_i^m < R_i^u$. A negative spillover implies that $(1 - R_i^m)^{A_i^m} < (1 - R_i^m)^{A_i^u}$ (see Equation 7). This condition holds when $A_i^m > A_i^u$ or by rearranging Equation 1, $[\ln(1 - B_i^m)/\ln(1 - R_i^m)] > [\ln(1 - B_i^u)/\ln(1 - R_i^u)]$. For a particular house, attacks can increase after mitigation. Suppose in the extreme case that all houses have an ignition probability of 1. Then the maximum number of attacks a house can experience before igniting is 1. Now suppose that all houses have been mitigated and have an ignition probability of <1. Now some houses will ignite after one attack but not all. If an attacked house does not ignite, it is still vulnerable to be attacked again.

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