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Integrated Framework for Wildfire Risk Mitigation Planning at the Wildland/Urban Interface

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DISSERTATION

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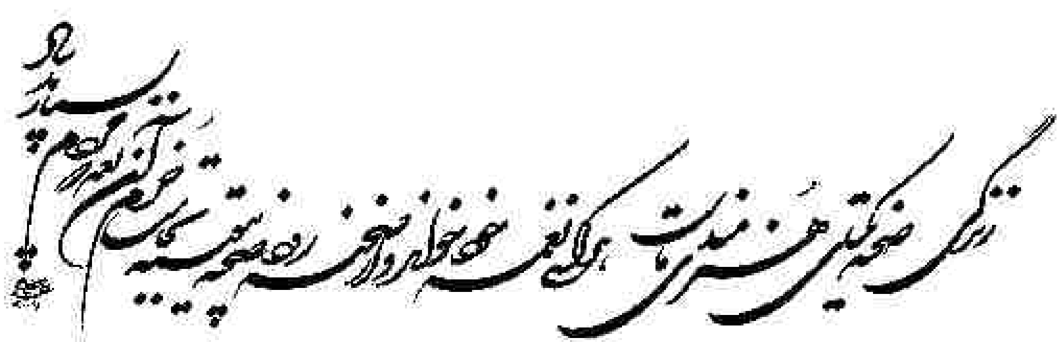
DEDICATION

In memory of my beloved grandfather, A. Khatibi.

His memories will remain forever in my heart.



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Abstract Past suppression-based wildfire management practices have increased the frequency and intensity of wildfires. Advocates for the re-introduction of natural wildfire regimes must also prioritize wildfire damage protection, especially for vulnerable communities located near forests. Areas where urban and forest lands interdigitate are called the Wildland Urban Interfaces (WUIs). In the United States, the area of the WUIs is increasing, making more people vulnerable to wildfires. By responding to four research objectives, this dissertation proposed and tested an integrated framework for wildfire risk mitigation decision making at WUIs. Decision makers who could benefit from the results of this dissertation include WUI homeowners, community planners, insurance companies, and agencies that provide financial resources for managing wildfire.

The first objective investigated the complex relationship between wildfire and property values in a WUI community affected by a catastrophic wildfire event. The analysis focused on evaluating whether the damage from a previous wildfire, and the risk from a potential future wildfire are negatively capitalized in the housing market of a WUI community. A

Hedonic Pricing Method (HPM) was applied on homes in Los Alamos County located in Northern New Mexico. Los Alamos is the home of a highly educated and high income community which experienced the Cerro Grande fire in 2000. Results showed that wildfire damage has a negative impact on the housing price, whereas future wildfire risk is a positive driver in the Los Alamos housing market. These findings support the wildfire mitigation paradox that states that WUI homeowners tend to underinvest for mitigating wildfire risk on their properties.

The second objective investigated the optimal investment required for mitigating the vulnerability of residential buildings to wildfire. The optimal retrofit plan for individual homes was estimated using an integer programming method. The evaluation function for this optimization is based on a multi-attribute vulnerability assessment system that yields a wildfire vulnerability rating for all properties in the study area. A feasible solution to this optimization problem is one that decreases the vulnerability rating of the house to an acceptable rating. Additional data included: (i) vulnerability assessment cards of the properties, (ii) building and site characteristics of the properties, and (iii) unit costs of implanting appropriate retrofit measure on each element of the property. These datasets were collected for 389 properties in Santa Fe County's WUIs. Using an integer programing model, the total cost of reducing the vulnerability ratings from "high" and "very high" to "moderate" vulnerability level was estimated for each property. To account for uncertainties in the costs of implementing a specific retrofit measure, a Monte-Carlo sampler was used to generate 2,400 cost scenarios from cost probability distributions. Using a regression analysis on the property data, a cost function for vulnerability mitigation through retrofitting was derived. The cost function allows estimation of the retrofitting cost per area of the house and considering the initial vulnerability rating of the house.

The third objective was to investigate wildfire optimal mitigation investment schedules for homeowners. Two types of investments for mitigation were analyzed, namely self-insurance and market insurance. Self-insurance is represented financially as the amount homeowners spend to implement retrofit measures to reduce their property's vulnerability to wildfires. Market insurance is the transfer of wildfire damage liability to a third party or insurance company. The investment decision of homeowners over a multi-year investment plan considering the effects of budget and market insurance policy constraints was formulated. The effectiveness of self-insurance improvements was modeled as a damage probability function. Using a mixed-integer programming model, the optimal annual investment for market and self-insurance was estimated. The case study in this chapter demonstrated the effect of various parameters on the investment schedule of honeowners. This case study considered the time value of money and insurance companies' contingency policies and budget constraints. The results showed that in the absence of budget constraints and mandates on mitigation, the homeowner's optimal choice would be to fully invest on insurance and to purchase the broadest wildfire hazard insurance coverage. When a minimum mitigating retrofit effort is required by insurance companies, homeowners would invest more at the beginning of the period and decrease their investment through time. In this case results showed that a homeowner would achieve a higher expected value of investment than a homeowner with whose investments increase through time.

In the fourth objective, an Agent Based Model (ABM) is proposed to account for

heterogeneity in homeowners' attributes and behaviors when confronting wildfire risk hazard. The success of the community to reduce wildfire risk was evaluated by aggregating the impact of each individual agent's behavior. The investment behavior of each homeowner for a five-year planning period was retrieved from the optimization model proposed in the third objective. A neighborhood of six homeowners was used to test the proposed ABM. When a wildfire occurs, the wildfire may or may not damage the property. Therefore, the loss accrued by each homeowner was stochastically simulated for each year in the simulation. The probability of loss was formulated as a function of the initial vulnerability rating of the property and the homeowners' cumulative investment on mitigation. The analyzed scenarios considered different types of homeowners (i.e. mitigating or non-mitigating). The spatial impact of neighboring properties on the loss potential of a homeowner was modeled using a conceptual fire spread model based on a Cellular Automata propagation model. Results suggest that (i) the location of the property in combination with (ii) the investment behavior of the homeowner influences the neighborhood's aggregate loss to wildfire. Policy-makers can better mitigate aggregate loss to wildfire by prioritizing certain locations over others.

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I. Introduction

1.1 Problem Statement

Wildfire is a complex natural hazard that unlike flooding, earthquakes and tornados is a process rather than a force (Cohen 1999). Human settlement in areas close to forests and natural, undeveloped settings, has changed wildfire from a natural process into a social-ecological process (Murphy et al. 2007); where human decisions and social structures are coupled with natural systems (Adger 2006). After practicing suppression-oriented wildfire management for years and experiencing an increase in the severity of wildfires due to fuel build-up, the current state of forest science suggests that sustainable wildfire management can only be achieved in the long term by re-introducing or restoring historical wildfire regimes (Taylor 2015). To re-introduce historical wildfire regime, protection of people, man-made assets, and properties is essential, and to some degree required by US laws and policies (Cooke et al. 2016). A variety of forest management strategies are used to protect people from catastrophic wildfires, including prescribed burns (Ryan et al. 2013) and forest thinning to ensure fuel disconnection from urban areas. Additional efforts include high-end ignition prediction and detection technology (Murphy et al. 2014), systematic wildfire-specific emergency management systems, and advanced fire suppression technologies (Villa et al. 2014). These approaches are mostly performed to ensure that human society is not exposed to the heat and embers of wildfires. Despite all the efforts to contain wildfire before it reaches residential communities, the concerns about intense wildfires with catastrophic consequences are increasing along with increases in residential losses to wildfire (Calkin et al. 2014). Whereas natural processes and climate change can impact the number and intensity of wildfires, population increase in wildfire prone areas is the main concern (Alexandria et al. 2016; Insurance Information Institute 2016).

Communities that are vulnerable to wildfire are the Wildland Urban Interfaces (WUIs). By definition, a WUI is where residential buildings and the undeveloped vegetated forest lands interdigitate (Radeloff et al. 2005). In the US, WUIs are spatially identified and mapped at the Census tract level, with the home density and vegetation layer as the main components for defining a zone as a WUI. Theobald and Romme (2007) showed that the area of WUIs increased by 52% in 3 decades since 1970, and predicted a WUI area of about 510,000 km^2 in year 2030. However, Martinuzzi et al. (2015) estimated that the area of the WUIs has already exceeded the predicted amount and it is about 770,000 km^2, with 44 million homes and a population of 99 million people. Haas et al. (2013) estimated that nearly 40 million people are facing serious wildfire threat.

Like many decision makers under risk, a homeowner's response to wildfire risk includes avoiding, transferring, reducing and accepting the potential loss to wildfire. Avoiding wildfire risk involves moving out of the WUI. Available statistics on WUI homeowners, however, show that rarely WUI homeowners move out even after nearby catastrophic fires (Price WaterHouse Coopers 2001), and there is no evidence of buy-outs due to heightened risk of wildfire. Among the three remaining options, this dissertation focuses on decision making for the mitigation and transfer of homeowner expected losses due to wildfire. It is believed that homeowner's efforts in averting wildfire losses can be up to 90% effective (Cohen 2000) when improving physical attributes of the property within 30-meter proximity of the building. In this dissertation, it is assumed that that the homeowner is a rational decision maker who seeks higher utility throughout their decision-making process. The utility of homeowners is mainly discussed in economic terms.

1.2 Goal and Objectives

The goal of this dissertation is to understand and decrease the impacts of wildfire on society by proposing and testing an integrated framework for wildfire risk mitigation decision making at the Wildland Urban Interfaces (WUIs). As a step toward this goal, four objectives are addressed:

- Investigate the gaps in social understanding of the risks and outcomes of the wildfire threat to call for policy and regulation intervention.(Chapter 2)
- Automate and optimize wildfire mitigation procedures across the planning landscape. (Chapters 3 &4)
- Improve wildfire behavior simulation models for studying the vulnerability of the built environment in the WUIs.
- Investigate of the use of agent based modeling to facilitate pattern recognition in wildfire related community under risk.(Chapter 5)

Chapter 2 investigates the housing market to test evidence of two socio-economical behaviors in a WUI with a substantial wildfire experience, Los Alamos, NM, through the estimation of a Hedonic Pricing Model (HPM). Through analysis of the variations in observed housing market values associated the damage of Cerro Grande fire of 2000, as well as risk of a future wildfires, the existence of social learning, or, alternatively, hazard mitigation paradox is investigated. Social learning occurs when a community develops an active pre-event preparedness to a natural hazard due to the experience of a previous disaster. This happens when community's collective memory of the previous disaster overcomes individuals' fading memories (Cutter et al. 2008). On the other hand, homeowners who are experiencing hazards such as wildfire, may be reluctant to invest adequate efforts in mitigation of their properties' vulnerability perhaps because they consider mitigation on the public lands and private lands as substitutions and not complementary (Steelman 2008; Prante et al. 2011; Crow 2015). Whereas the public land manager has to ensure protection of the communities, homeowners are only encouraged to do so on private lands. Los Alamos is known to be home to a highly educated, high-income population, and is considered in this study as a test case for the occurrence of social learning after Cerro Grande fire of 2000 that cost over 1 billion dollars in damages.

To answer how much investment is required from homeowners, Chapter 3 evaluates the optimal amount of mitigation expenditure to reduce the vulnerability of homes from high or very high vulnerability to moderate vulnerability and less is calculated. The study area in Chapter 3 is Santa Fe County using vulnerability assessment data collected by Santa Fe County's fire department. To assess the vulnerability of homes, elements of the land and building that contribute to the total vulnerability of the property to wildfire are listed and the vulnerability score of each element is assigned through site visits. The total vulnerability score, as the sum of the scores assigned to all elements, is classified based on a scale proposed by wildfire experts to interpret vulnerability score to descriptive levels of vulnerability (low, moderate, high, etc.). To reduce the vulnerability of the properties, the optimal schedule of the improvements that can reduce the total score below the threshold of moderate vulnerability is drawn by applying an integer programing method. Due to uncertainties in the costs of improvement, a Monte Carlo sampler is coupled with the integer programming. For 715 properties, the optimal costs of vulnerability mitigation given 500 samples of cost are estimated providing mitigation's optimal cost data set. Descriptive statistics of the resulting data population are derived and reported. Finally, a logarithmic mitigation cost function is fit to the results that return the average optimal amount of investment estimated as a function of the reduction of the vulnerability score. Results indicates that on average, for our sample of 360 residential buildings the minimum total cost of implementing retrofit measures to moderate vulnerability is in the range of [$0, $27,000].

Chapter 4 expands the analysis in Chapter 3 by finding an optimal time schedule for investments on both mitigation and insurance in a multi-year interval. In this chapter, it is assumed that homeowners spread their mitigation investments over time and not all-at-once. The other assumption is that given their financial constraints, homeowners combine their decision on self-insurance (mitigation) with insurance premium purchased to cover potential losses due to wildfire. In other words, they make a trade-off between loss aversion and risk transfer each year. A mixed integer programming approach is used to determine the optimal annual amount of self-insurance investments and private insurance premiums.

Chapter 5 aims to analyze the behavior of individual homeowners at the community level and to introduce a measure of community success when confronting wildfire hazard.

An economic resilience index is used for assessing the collective return of homeowners' investments on self-insurance and private insurance in a given community. The economic resilience index measures the percentage of loss averted from total maximum potential loss (Rose 2005). An agent based model is proposed to simulate the behavior of homeowners considering their differences in home value, vulnerability, and location. A wildfire event is simulated using a Cellular Automaton concept, to estimate the potential losses accrued on each homeowner. The wildfire simulation has a stochastic nature and accounts for spatial externalities. For each year, community investments and the economic resilience index are calculated given the investment decisions from Chapters 2 and 3, the divergence from optimal investment plan due to a certain stressor and its impact at the community level can be investigated using the proposed model.

Chapter 2 and Chapter 5 are proposed for policy research whereas Chapter 3 and Chapter 4 attempt to find answers to computational optimization problems. Chapter 2 suggests that homeowners may underinvest on wildfire mitigation, which leads to the question of "what is considered to be adequate investment?" which is addressed in Chapter 3. The results of Chapter 3 are used in Chapter 4 to account for the dynamic nature of homeowner investment, as well as for the tradeoff between self-insurance (mitigation) and insurance investment. Chapter 5 combines Chapters 2 and 3 considering multiple agents to test the impact of individual investment decision on the community's success when confronting wildfire. These connections are illustrated in Figure 1.

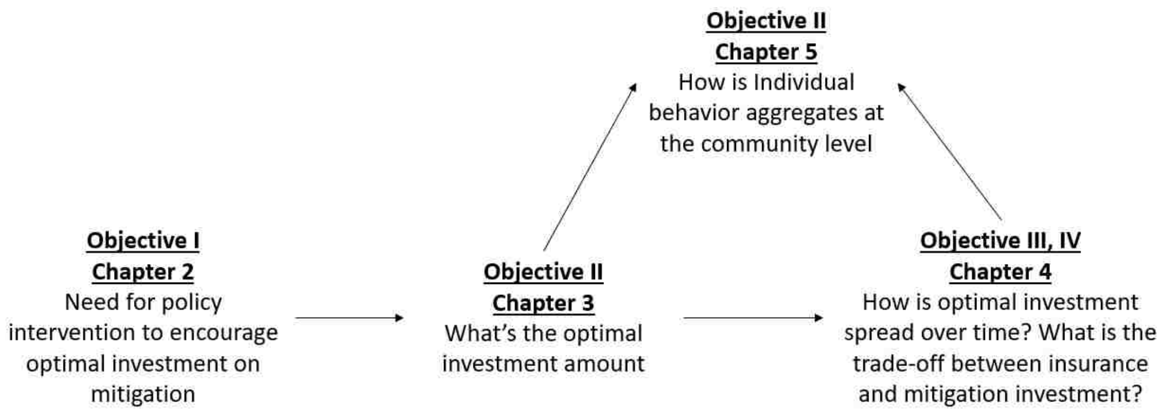

Figure 1: Connection between Chapters

II. Evidence of Social Learning? The Effects of both Historical Wildfire Damage and Future Wildfire Risk on Housing Values

Abstract: In this analysis, a hedonic pricing model is applied to estimate the impact of two attributes of wildfire on housing values in the Wildland Urban interface (WUI): (i) a burn scar, representing the disamenity of a highly salient historical wildfire event; and (ii) the latent risk of a future wildfire. The investigation uses a GIS dataset, including the burn scar viewshed and a fairly sophisticated wildfire risk measure matched with geo-coded assessments of property values in the surrounding the city of Los Alamos, New Mexico (NM), USA, where the Cerro Grande Fire of 2000 was a landmark wildfire disaster. Spatial econometric results indicate that the fire scar lowers the value of a typical house in our sample by 2.5 percent. In contrast, the mean risk of a future wildfire actually raises the value of a typical house by 0.4 percent. Rather than evidence of social learning, as the market would correct to better reflect fire hazards, results support the wildfire risk mitigation paradox, where private landowners continue to underinvest in risk mitigation.

Keywords: hedonic pricing method, property values, risk mitigation, wildfire

1. Introduction

Both human and natural factors (e.g., drought, climate change, grazing, and fire suppression policy) have contributed to increases in the frequency of high-severity of wildfires in many forested mountain regions in the Southwestern United States (US) and elsewhere (Swetnam et al 2016; Westerling 2016). This high risk coupled with the expansion of Wildland Urban Interface (WUI) areas (Radeloff et al. 2005; Evan et al. 2015) has led to an increased need for sustainable wildfire management policy (Steelman 2006). Heavy reliance on suppressing wildfires has been shown to incentivize WUI development, further raising the cost of fire suppression (Olmstead et al. 2012; and Gude et al. 2013). Alternatively, emphasis could be placed on protecting people and property while implementing a combination of long term restoration of historical wildfire regimes and short term hazardous fuel mitigation in the interface of public and private lands (Steelman 2006; Little et al. 2015, Taylor et al. 2015). Unfortunately, this strategy is challenging because individual homeowners' protection decision is based on their perceived risk of wildfire (Talberth et al. 2006; Meldrum et al. 2015), which can be conflated with the desirable amenity perception of a dense forest (Donovan et al. 2007; Hjerpe et al. 2016). Additionally, the failure of a homeowner to mitigate imposes a risk externality on neighboring properties (Crowley et al. 2009; Busby and Albers 2010; Meldrum et al. 2014), and individual homeowners may free ride on the risk reduction efforts by others, including any public efforts (Prante et al. 2011, Busby and Albers 2010). This underinvestment in risk reduction by homeowners has been referred to as the wildfire risk mitigation paradox (Steelman 2006; Little et al. 2015).

This investigation explores the complex relationship between wildfire and housing values in a WUI community with significant past experience with a catastrophic wildfire disaster. The landscape has a large, noticeable burn scar, and a significant need for hazardous fuels reduction in the larger region (see discussion in Adhikari et al. 2016). Thus, this WUI community jointly exhibits indicators of both ex-ante risk and ex post damage. Homeowners' perceptions of a catastrophic fire might lessen with time. But, consistent with a social learning hypothesis (Cutter et al. 2008), in a fire-adapted WUI community (Evan et al. 2015), we might expect that the need to reduce risk would not be collectively forgotten. If such learning is present, then evidence might be increased mitigation activities (e.g., Evans et al. 2015), and presumably detected in market signals such as house prices (where higher risk might lower value).

The objective of this analysis is to apply a hedonic pricing model (HPM) to decompose the impact of wildfire on housing values in the WUI. In contrast to the majority of prior HPM studies focusing on either the realized effects of wildfire in the WUI <u>or</u> the risk of future fires, this analysis simultaneously investigates the effects of both: (i) a burn scar, representing the disamenity of a highly salient wildfire event; and (ii) the latent risk of a future wildfire event. This investigation uses a relatively unique WUI data set and location, and implements a sophisticated method for capturing wildfire risk. We use the Flammap software (Finney 2006), which is a wildfire risk assessment program that takes into account complex interactions between climate, topography and landscape fuel. Then, GIS data, including the burn scar viewshed and wildfire risk are matched with geo-coded assessments for property values from the WUI study area surrounding the city of Los Alamos, in the Jemez Mountains of New Mexico (NM), USA.

The area is unique in that: (i) Los Alamos is a relatively affluent and educated, scientific community located on an isolated forested mesa; (ii) the surrounding Jemez Mountains area have an extremely well-documented scientific record of human interactions suppressing frequent fires, and creating high-severity fires' risk through fuels build-up (e.g., see Swetnam et al. 2016), including nearby recent extreme fires (e.g., Los Conchas in 2011); and (iii) the Los Alamos community was subject to a past landmark wildfire disaster -- the Cerro Grande Fire of 2000. The fire was started as a prescribed burn involving the National Park Service, when adverse atmospheric conditions caused the fire to burn out of control destroying about 250 houses, as well as dozens of non-critical structures at the federal Los Alamos National Lab (LANL), nuclear weapons design facility, leaving 194.2 km^2 of burnt landscape (Figure II-1) (Hill 2000; FEMA 2001; GAO 2001).

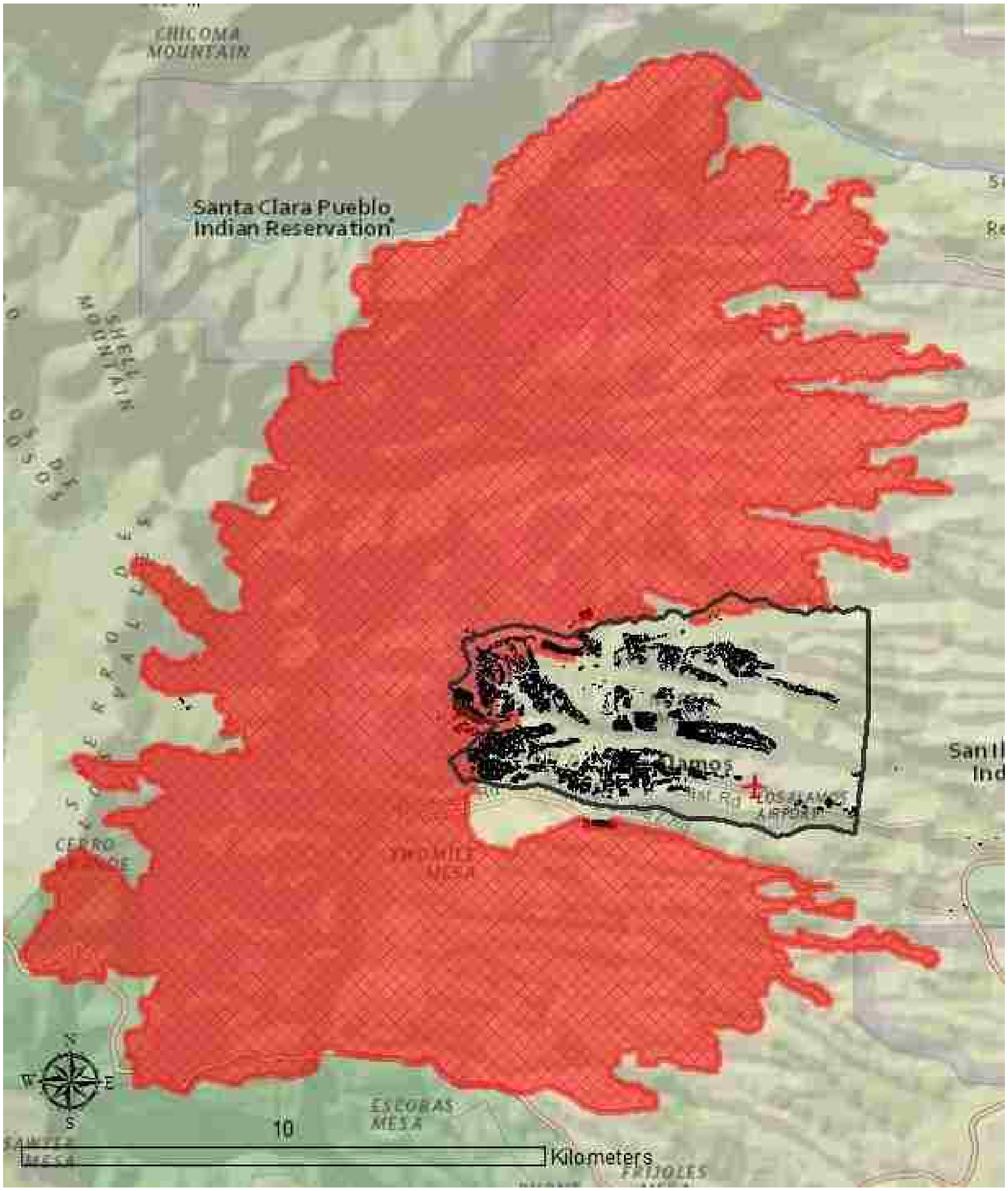

Figure II-1: The burn scar perimeter of Cerro Grande (indicated by red color), black spots are houses in or around Los Alamos, NM

Spatial econometric results show that, as expected, the visual disamenity of the fire scar negatively impacts property values, lowering the value of the average house in our sample by approximately 2.5 percent. However, even with this evidence -- a visual and monetary reminder of the negative consequences of wildfire, wildfire risk is not negatively capitalized into housing values. Rather, ex-ante wildfire risk has a positive effect on housing prices (0.3 percent for the average house). While inconsistent with social learning in a fire-adapted community, this result is consistent with the wildfire risk mitigation paradox. Hence mitigation efforts by homeowners may be inadequate. This puts pressure on public budgets to continue to overinvest in increasingly-costly fire suppression to protect people and properties. Finally, possible public policy interventions to change risk perceptions, better incentivize homeowner risk mitigation, and finance an increased scale of forest restoration are discussed.

2. Background

2.1. Wildfire Risk and Community Resilience

The risk exposure of a property to wildfire can be thought of as the probability of a wildfire ignition event, times the probability of the wildfire arrival at and damaging a parcel (due to radiation, combustion, or flying embers), times the magnitude of loss given the property conditions (McKee et al. 2004; Chuvieco 2010; Prante et al. 2011; Little et al. 2015). In the context of wildfire hazards, risk mitigation refers to all efforts or actions to reduce this risk exposure – the potential impact of the wildfire on people (see Brenkert-

Smith et al. 2015). These efforts may include implementing retrofit measures on the building's exterior (e.g., fire resistant materials) and surrounding landscape (reducing dense, fire prone vegetation in the "home ignition zone" near the property), and at a broader scale can include forest treatments (such as mechanical thinning and prescribed burns).

As recently noted by Smith et al. (2015, p. 1) "changes in temperature and precipitation are expected to increase the likelihood and severity of wildfires in the western USA" (and see Westerling et al. 2006; USDA 2015; Liu et al. 2015). Not surprisingly then, public wildfire suppression costs have grown significantly over the last several decades, especially in the western US, with its large percentage of public forestlands. With the expansion of the WUIs, suppression efforts become costlier and more complicated (Gude et al. 2013). For example, for the U.S. Department of Agriculture's Forest Service, the annual cost of fire suppression activities has regularly gone over $1 billion, and is projected to grow to $1.8 billion by 2025 (USDA 2015), this has often come at the expense of preventative, hazardous fuels reduction and forest restoration efforts (USDA 2015). Thus, as climate change has lengthened the wildfire burn season, needed risk mitigation efforts have lagged. This combination leaves many forested communities vulnerable to wildfire risk, and the economic, social and environmental costs of high severity, catastrophic wildfires can be significant (e.g., see review in Evans et al, 2015).

If risk mitigation efforts are connected to ecological restoration prescriptions, rather than simply reducing all vegetation and fuel loads (see Allen et al. 2002; Taylor et al., 2015), then they can provide ecosystem services and improve forest health, adding to the value of public forests that serve an ecological and economical region beyond the nearby WUIs forest health may be reflected in a kind of "good fire versus bad fire" trade-off (Kaufman et al. 2005). Frequent, low-severity fires generate many ecological benefits, while reducing fuel loading. In contrast, altering natural fire regimes through intensive suppression of all fires creates significant high-severity wildfire risk exposure to interconnected natural and human systems (Allen et al. 2002). Specifically, scientists forecast a lengthening fire season and increasing wildfire severity in the Southwestern region of the US (Liu et al.2015; Westerling et al. 2006; Westerling 2016). In the semi-arid, fire-prone ponderosa pine forests prevalent in the Jemez Mountain region of Northern New Mexico, Swetnam et al. (2016) document the long history of human interactions on the landscape, altering the natural fire regime of frequent surface fires. In their study of how wildfire risk in northern New Mexico forests affects communities (including those downstream with threatened drinking water security), Adhikari et al. (2016, p. 4) characterize the sustainability problem as follows:

We have significantly altered forest ecosystems in a negative way (degraded natural capital) increasing catastrophic wildfire risk while at the same time more and more people (and their physical capital) are moving into flame zones, and there remains considerable policy gridlock on suppression versus hazardous fuels treatments. How do we reintroduce natural fire regimes at landscape scale while protecting at-risk communities and shift a greater proportion of costs away from federal taxpayers (in suppression costs) and onto communities (paying for ecosystem services) and homeowners (mitigation and insurance), while considering social equity and building social capital?

Against this broader backdrop, understanding whether and how housing markets in the WUI are capitalizing wildfire risk emerges as an important piece of information in understanding and addressing this sustainability challenge.

Cutter et al. (2008) view resilience, as both a process (rather than an outcome), and as central to understanding sustainability. While multiple definitions exist, Cutter et al. (2008, p. 599) define resilience as “a system’s capacity to absorb a disturbance and re-organize…” That re-organization may not necessarily be to a prior state, but rather can include community adaptations that allow improved coping with future disturbance events (e.g., wildfires). Thus, it allows for social learning, defined as the diversity of adaptions that promote and allow mechanisms for collective action (Cutter 2008, p. 603; and Adger et al., 2005, p. 1038). Social learning overcomes individual memory, which may fade (e.g., as a burn scar fades), and helps lock in improved pre-event preparedness. In Cutter et al.’s (2008) proposed model for tracking or measuring the “disaster resilience of place”, they list several dozen possible candidate measures for community resilience indicators, including *property values*. But, as we explore below, the relationship between wildfire and property values is complex.

2.2. Wildfire and Property Values

A classic tradeoff in rural housing markets is the potential amenities to homeowners living close to the wild or “uninterrupted” settings, contrasted with possible increased risk from disturbance events, such as wildfires, floods, landslides etc. Such tradeoffs can commonly occur in the WUIs, where residential development meets the private and public wildland (Davis 1990). Similar to flood plains or flood zones, this adjacency of forested land and the urban (or suburban) built environment can be thought of as flame zones, where private properties are located in areas vulnerable to high severity wildfires.

In the US, WUIs increased 52% in size, from 1970 to 2000 and have been predicted to increase 10 more percent by 2030, adding up to more than 510,000 square kilometers (Theobald and Romme 2007). In the western US, almost 90% of WUIs have been categorized as high severity forest fire regimes (Theobald and Romme 2007). Recent estimates place the size of the WUI in the US at 770,061 km^2 (190 million acres), 44 million homes and 99 million people (Martinuzzi et al. 2015), with nearly 40 million people at significant risk (Haas et al. 2013).

In many forested settings, high intensity, stand-replacing fires can lead to more high severity fires in rapid succession (Gray and Franklin 1997). High-intensity fires that have gone out of control due to adverse conditions, defy community boundaries and put people and their property at risk (Cohen 2010; Keiter 2006). While land managers are constantly dealing with wildfire risk and incidents of different sizes throughout wildfire season, WUI residents make risk mitigation decisions based on their subjective assessment of the risk to their property (Talberth et al. 2006), which may differ significantly from expert assessments (Meldrum et al. 2015). Further, homeowners may treat mitigation, insurance and expected suppression as substitutes rather than complements, and public agency risk mitigation efforts in an interface region may "crowd out", rather than increase, private mitigation participation and levels (McKee et al. 2004; Berrens et al. 2008; Busby and Albers 2010; Prante et al. 2011; Busby et al. 2013).

Hedonic Pricing Method (HPM), is a revealed preference technique, compared to the stated preference techniques (e.g. Willingness to Pay estimated (Mozumder et al.

2015)), and has been used to evaluate the value of non-rated values such as flood hazard, storm water run-off (Boatwright et al. 2013), and river pollution (Chen et al. 2017). To evaluate the impact of wildfire, the HPM is a well-established technique (see review in Hansen, Mueller and Naughton, 2014). The objective of the HPM is to empirically estimate the marginal implicit value or prices embedded in home buyer/seller tradeoffs; this is done by statistically decomposing the observed variation in house prices (Taylor 2003). In terms of the impact of wildfire, a number of pre-post studies have evaluated the drop in sales prices of houses that are not physically damaged but proximal to past wildfire events (e.g., Loomis 2004). This is also done using more descriptive or less rigorous statistical methods; including studies of the housing market in Los Alamos before and after the 2000 Cerro Grande Fire, which documented 3 to 11 percent declines in regional home prices (FEMA 2001; Price Waterhouse Coopers 2001).

Additionally, HPM is a useful tool for investigating the implicit prices of ex-ante wildfire risk characteristics (Hansen et al. 2014). A recent example is the four-city western US study of Hjerpe et al. (2016). Ceteris paribus, house values are highest with low density within 100 meters, but increase when going from medium to high density. Within the broader 500-meter context, "WUI homebuyers prefer to be close to higher forest density and higher wildfire risk areas." Hjerpe et al. (2016) call for further studies, and note that they were unable to include recent wildfire effects in their sample sites. Further, with their mixed set of results, they note that, a priori, it is not clear whether wildfire risk will be capitalized as a negative value in housing valuation, as dense forest vegetation and amenity values may be conflated with risk measures. This blending of forest amenity characteristics and wildfire risk was argued to be present in an HPM study by Donovan et al. (2007). Using Colorado Springs, CO housing data that included publicly-assessed wildfire risk ratings for each property, Donovan et al. (2007) found distinct market effects before-versus-after a public agency internet posting of the property ratings. Before the information was posted, the property ratings were positively capitalized into housing values, which suggested that amenity effects of dense forest vegetation outweighed any perceived wildfire risk (see Stetler et al. 2010). But, after the information posting, the risk rating was no longer a significant determinant of house values.

Further, Loomis (2004) and Reily (2015) suggest that home buyers/developers are incentivized to continue to live and build in flame zones when both the physical damage due to a wildfire event and the loss in property values that happen after that event are compensated. Such factors may be of concern with the Cerro Grande Fire of 2000. The federal Cerro Grande Act was passed in 2000 to compensate the victims of that fire, and about $1 billion was distributed (Hill 2000; GAO 2001), with only an estimated 10 percent of affected households moving out of the county (Price Waterhouse Coopers 2001).

The majority of HPM studies related to wildfire examine either the effects of past wildfire(s) or some indicator of the ex-ante risk of a future wildfire. One noteworthy exception is Stetler et al. (2010), who used HPM on property values in northwest Montana (1996-2007) to study the impact of both a set of burn scars (view and proximity to) of 0.04 km^2 (4 ha) and larger, and a vegetation measure -- the density of forest canopy cover near the home. The latter was viewed as both a "proxy for visual pleasantness and potential wildfire threat" (Stetler et al. 2010, p. 2238). Stetler et al. (2010) found significant negative impacts of burn scars on housing prices and that at least for within 250 meters, "the amenity aspect of trees, including shade, privacy and aesthetic value, outweighs disamenities such as wildfire risk for trees… close to a home" (Stetler et al. 2010, p. 2238).

Although Stetler et al. (2010) considered both damage (burn scars) and a vegetation (forest canopy cover) measure of wildfire risk, the coincident effects of both attributes of wildfire in the housing market remains an open research question (Hjerpe et al. 2016). The impact of any given fire on reducing future wildfire risk is not well known. Ecologically, even after an incident, wildfire threat remains, and may even escalate in some settings (Peterson 2002; Hansen et al. 2014). When accounting for wildfire risk in HPM, the selection of the risk measure is important. There is not a universally agreed-upon wildfire risk measure, and researchers have used measures based on subjective judgment or data availability. For example, Stetler et al. (2010) used canopy cover, and Donovan et al. (2007) used local fire department property assessments.

Finally, another important aspect of modeling the impact of wildfire on property values is accounting for spatial interdependencies between proximal properties (Donovan et al. 2007; Hansen, Mueller and Naughton 2014; Hjerpe et al. 2016; Mueller and Loomis 2008, Mueller et al. 2009). In the presence of spatial error, neighboring parcels can share values of some of the unobserved variable (Dubin 1988), which can result in error or bias in the estimation and interpretation of HPM results in some cases (Brasington and Hite 2005).

To extend this limited, but important literature, our study area, Los Alamos, is revisited where the scar of a salient past wildfire event and the risk of a future wildfire co-exist. The question to be answered is whether, after more than a decade from a destructive wildfire, there is any evidence that social learning has taken place, in the sense that past fire experience has been transformed into evidence of collective market awareness about future risk?

3. Study Area and Data

The focus of this study is on the city of Los Alamos, NM. The isolated forest mesa is part of the explanation for the original location of the Los Alamos National Laboratory (LANL) nuclear weapons development facility, for which the city is most famous. The total population of the city in 2010 was 12,019, with median age of 43.5, and 73.8% having a post-high school degree (associate, bachelor or graduate). The main employer in the area is LANL with over 10,000 direct employees. Accordingly, Los Alamos is a high income, highly-educated community. The median and mean annual household incomes of the population are $106,016 and $116,563, respectively. While there are other pockets of affluence (see Talberth et al. 2006; Hjerpe et al. 2016), many southwestern forest communities might be considered much more vulnerable in the sense of understanding the risk, and being able to afford mitigation (Lynn 2003).

In terms of housing, 5,289 households reside within the city, and there is a slightly higher number of total houses (5,863). The difference between households and houses is unoccupied houses (574 units), including 221 seasonal and recreational houses. Also, in terms of ownership, 3,662 houses are owner occupied and the rest are mostly rented. Geographically, Los Alamos is located on Pajarito Plateau and is adjacent to the Bandelier National Monument, Valles Caldera National Preserve, and parts of the Santa Fe National Forest. The town is dominated by medium density WUI with 5 to10-year fire return interval in a ponderosa pine and mixed conifer surrounding ecosystem (Farris et al. 2013).

In this study, data for the year 2013 were obtained from two main sources (i) the Los Alamos County Assessor's appraisal survey data; and (ii) the office of GIS services at the Los Alamos County office. All assessed properties are identified using their tax ID's both in the surveys and the building foot print map layer, facilitating connection between the two data sets.

Assessed values are used to proxy home prices, as done in a number of other HPM studies (see Taylor, 2003), for several reasons. First, in terms of simple availability, NM remains a nondisclosure state, and does not provide public access to real estate prices. Hence, the assessed values remain to be the only available valuation in the study state; although, by the NM state constitution, property taxes must be based on market prices (Berrens and McKee 2004). Second, minimal population growth and change in the area, given its location on top of a forested mesa and surrounding federals lands would limit the number of transactions for application of HPM. Third, superiority of sales data over assessed values in revealing the value of structural, neighborhood, and environmental attributes of the homes has been subject to debated (Freeman 2003; Kim and Goldsmith 2009; Ma and Swinton 2012; Hansen et al. 2014)

All of the building characteristics are found in the county assessor's survey dataset. Neighborhood and wildfire data are calculated, using building footprints and pertinent spatial layers, namely trails network, golf course location, Cerro Grande fire burn scar polygon, Digital Elevation Model grid data (DEM), and a crown fire potential map. The focus of this analysis is on WUI areas and non-WUI areas are excluded. WUIs are identified at the Census tract level (Radeloff 2005) with the last updated WUI maps published in 2010. Also, following Mueller and Loomis (2008), houses smaller than 46.5 m^2 (500 ft^2), those with less than 538 $/$m^2$ (50 $/ft), and those with zero bathrooms are excluded. In addition, houses assessed below $95,000 are excluded. Below this represents a clear cut-off point for low-quality housing in the local market and was selected based on discussions with local realtors.

Table II-1: Variable Descriptions

Variable	Description
P	Assessed Value of the house, 2012 USD, Santa Fe County Assessor's office, in Year 2013
$AREA$	Area of the house (m^2)

$2 + BATHS$	Dummy variable for whether the house has more than 2 bathrooms (1 = Yes, 0 No)
$GARAGEAREA$	Garage Area (m^2)
$HIQUALITY$	Dummy variable for whether the construction quality is greater than 4.5 on 1-6 scale, where 6 is high and 1 is low (1=Yes, 0=No)
$FIREPLACE$	Dummy variable for whether the house has a fireplace (1=Yes, 0=No)
$DECK$	Dummy variable for whether the house has a deck (1=Yes, 0=No)
$POORROOF$	Dummy variable for whether the house has asphalt shingle, or wood shake and shingle as roof system (1=Yes, 0=No)
$DIST - TRAILS$	Closest Euclidean distance (m) to the trail network
$DIST - GC$	Euclidean distance (m) to the municipal golf course
$DAMAGE$	Percentage of area of wildfire burn scar visible from the house's location
$RISK$	Area (m^2) of crown fire risk-bearing land within the HIZ

Los Alamos County surveys a variety of building characteristics annually that includes basic characteristics of the homes from area and number of rooms to the types of the roofing systems. Los Alamos homes are ranked based on their construction quality on a 1-6 ranking basis. The variable, $HIQUALITY$ is defined to identify relatively high quality building structures. Thus, the value of one for $HIQUALITY$ is assigned to houses with construction quality of 4.5 or higher. The existence of a fire place and a deck are represented in the dummy variables, $FIREPLACE$ and $DECK$, respectively.

FEMA (2008) indicates roof systems with asphalt shingles, wood shake and shingles as not showing adequate resistance to wildfire embers and heat and encourages change of such systems. The dummy variable $POORROOF$ indicates the presence of one of these unsuitable roof systems. Additionally, Los Alamos has a complex trail network. The distance of each house to the closest trail in the network is calculated by the "NEAR" tool in ArcGIS. Using the spatial layers of trails network and building footprints, this tool finds the closest trail to the house, and returns the Euclidian distance between the house and that trail $DIST-TRAILS$, in meters. Similarly, distance (in meters) to the main municipal golf course, $DIST-GC,$ is calculated using the NEAR tool.

Two wildfire attributes emphasized in this model are: (i) the ex post damage measure of the view of the Cerro Grande (2000) burn scar; and the latent or ex-ante wildfire risk measure of crown fire potential. Below, we detail how each of these is measured for the HPM. The variable $DAMAGE$ represents the portion of the total scar of Cerro Grande fire that is visible from the standpoint of each building, which is calculated using the VIEWSHED tool in ArcGIS10. Specifically, this tool receives the location of an observer point and the elevation of the landscape on which the observer and area of visual interest are located and returns a binary raster output. In order to gain more accuracy in estimation of the view on Cerro Grande fire scar, the building heights are added to the DEM layer. In a raster format, the landscape is divided by a mesh of grids, and each grid has a value pertaining to the subject of the map. The output of VIEWSHED is a binary value for each grid. The value assigned to the output grid is 1 if there is no obstacle in the line of sight (between observer and object). If the grid is obscured by terrestrial barriers, the grid will receive a null value. In order to calculate the view on burn scar, the extents of the landscape are set to the polygon of the Cerro Grande scar. Figure II-2 depicts the view on Cerro Grande fire scar from the location of a random house in Los Alamos.

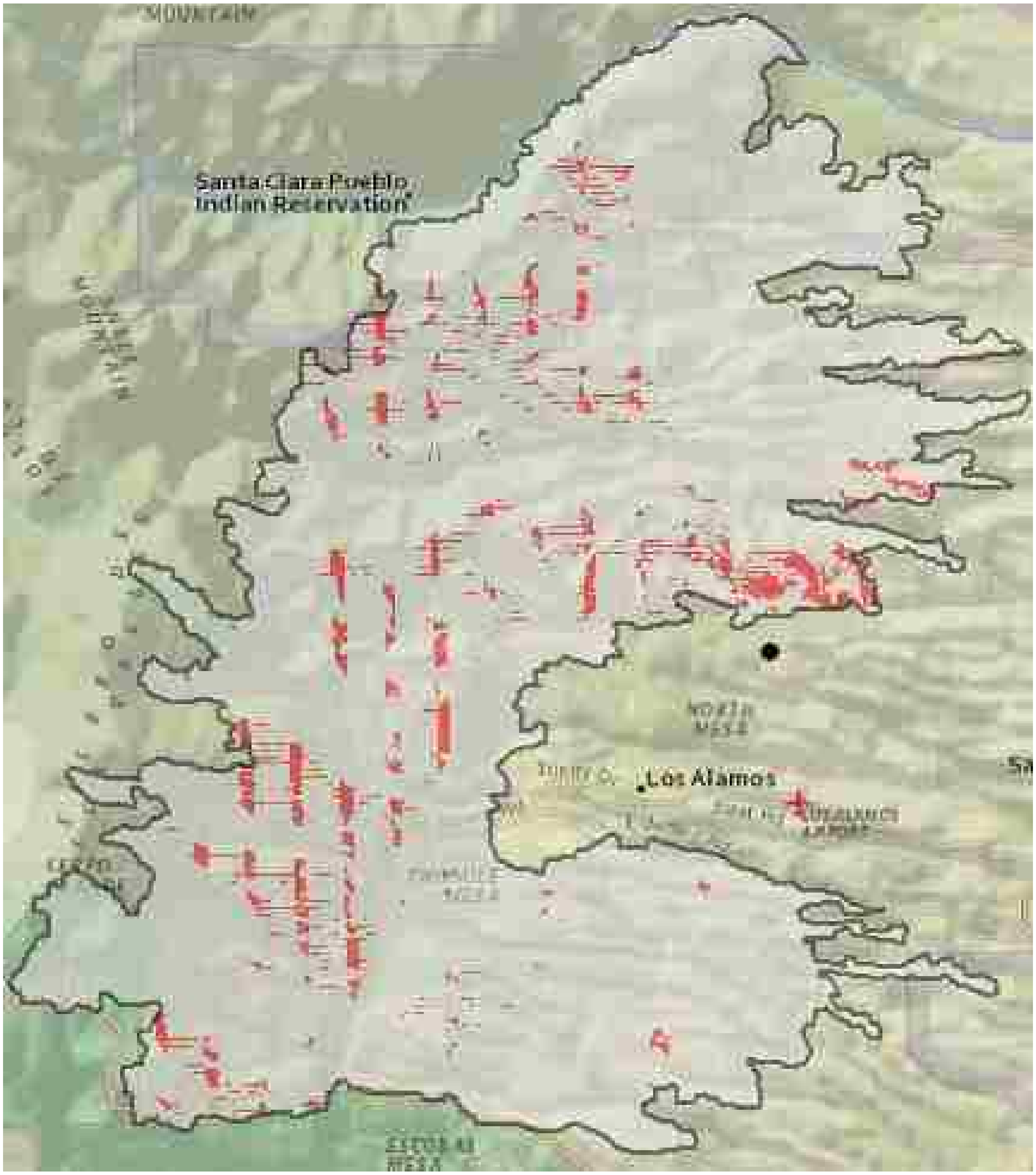

Figure II-2. Viewshed tool output, the indicated black dot is the location of one of the houses in Los Alamos. The grey polygon is the burn scar of Cerro Grande fire; the red marks within the scar polygon are grids that are visible from the given house's location

The variable $DAMAGE$ is calculated by dividing the number of visible grids inside the scar polygon divided by the total number of grids, about 4.8 million grids with 6m by 6m size. Compared to the with/without view on a fire scar dummy variable used by Stetler et al. (2010), it is believed that this measure gives more information about the impact of the burn scar by giving the extent of the view.

The analysis incorporates ex-ante wildfire risk, using the variable $RISK$ to represent the area of land cover that carries crown fire potential in the proximity of a given house. This begins with a canopy fire potential map originated by Forestry Division of New Mexico's Energy, Minerals, and Natural Resources Department (EMNRD). Among other types of fire, canopy fire has been the major cause of home ignition and destruction in WUIs (Cohen 2000). A canopy fire potential map is produced by wildfire experts as an outcome of the FlamMap software (Scott 2006, Finney 2006, Stratton 2004), and allows the area of land that poses a threat of building ignition to be attained. FlamMap utilizes vegetation, terrestrial, and atmospheric characteristics of the location of study to along with other measures of potential wildfires. The fuel layers specifically compatible with Flammap software are generated, on a national scale, by the Landfire Program (Landfire 2016); the fuel layer used for this study pertains to year 2012. Thecrown fire potential map has a raster format, where values are of binary type (1 for grids assessed to have crown fire potential and 0 otherwise). The size of each grid is 30m by 30m. Given the lattice of the landscape, the total risk attributed to each house is the total area of grids with risk bearing value of one within the Home Ignition Zone (HIZ). HIZ is the building and its surroundings within a 30-60 m distance (Cohen 2001), where buildings are the most susceptible to ignitions caused by wildfire embers as well as heat flux. Canopy fires within the HIZ pose the greatest ignition risk to the building. Through laboratory tests, it is shown that clearing the HIZ from potential fuels, specifically vegetation, reduces the home ignition probability by about 90% (Cohen 2000c). It is also shown that the clearing the HIZ from the fuels is the most cost effective measure homeowners can implement to reduce their homes' vulnerability to wildfire (Stockmann 2010).a (Shafran 2008). To calculate $RISK$, for each house, the number of risk bearing grids (i.e. grids on the canopy fire potential map with value of 1), are counted within each house's Parcel boundary and HIZ. The area with canopy fire potential within the HIZ is the counted number of risk bearing grids times the area of each grid (900 m^2).

4. Modeling considerations

The HPM has its roots in neoclassical economic theory (Rosen 1974; Taylor 2003). In defining houses as heterogeneous goods, HPM is an indirect way to isolate the implicit value or prices embedded in home buyer/seller tradeoffs between different characteristics offered in the residential house market. Absent any fees for repackaging house characteristics, the house price is the sum of implicit prices of its component characteristics (Taylor 2003), which may include both environmental amenities and disamenties or hazard risks. It is assumed that home buyers are willing to pay more (less) for increments (decrements) in environmental goods and services (Mueller, Loomis, and González- Cabán 2009). Thus, as a type of revealed preference approach, HPM's of housing markets have been extensively used to find the value of non-market environmental characteristics (Harrison Jr and Rubinfeld 1978; Mueller, Loomis, and González- Cabán 2009; Richardson, Champ, and Loomis 2012; and Stetler, Venn, and Calkin 2010).

Following Taylor (2003), the basic theory of the HPM is briefly presented as follows. Let $\underline{\mathrm{Z}}$ represent a bundle of house characteristics ($\underline{\mathrm{Z}} = \mathrm{Z}_1, \mathrm{Z}_2, .., \mathrm{Z}_\mathrm{n}$). It is assumed that in a perfectly competitive market, the price schedule associated with a house identified by bundle $\underline{\mathrm{Z}}$, denoted by $\mathrm{P}(\underline{\mathrm{Z}})$, reflects equilibrium reached through interactions between buyers and sellers. Buyer j tries to maximize his utility, U^j, while limited by his available budget, Y^j. The objective of the buyer is to maximize his utility that is composed of the bundle $\underline{\mathrm{Z}}$ and all other goods, denoted by X, $U^j(\underline{\mathrm{Z}}, \mathrm{X})$; and the budget constraint is shown as follows:

$$Y^j = \mathrm{P}(\underline{\mathrm{Z}}) + \mathrm{X} \qquad \text{Eq. II-1}$$

Where X represents the numeraire good with a unit price (i.e. $\mathrm{P(X)} = 1$). For buyer j, maximum utility is reached if (i) the rate of substitution of Z_i for X equals the ratio of marginal utility of Z_i to that of X; and, (ii), the marginal price of each characteristic is equal to the marginal bid the buyer places for that characteristic. Similarly, a seller's utility is maximized when the marginal price for that characteristic is equal to the marginal cost of providing that characteristics. Ideally, a house price schedule manifests the points of balance between bid and offer functions for all characteristics. Specifically, the general relationship between the price of the home in the WUI and it's structural, neighborhood and environmental variables can be generically represented as

$$P = f(H, N, WF) \quad \text{Eq. II-2}$$

Where, P is the sales price or assessed value of the house; H represents a vector of structural and property characteristics, N indicates a vector of neighborhood descriptors and WF is the vector of wildfire attributes. A wide variety of specifications and functional forms can be used to estimate a HPM (Taylor 2003), and numerous specifications and functional forms were investigated here in terms of goodness of fit. Similar to Mueller and Loomis (2008) the semi-log regression form was adopted, along with the following specification:

$$\begin{aligned} \ln(P) = \beta_0 + \beta_1 \times AREA + \beta_2 \times 2 + BATHS + \beta_3 \\ \times GARAGEAREA + \beta_4 \times HIQUALITY + \beta_5 \\ \times FIREPLACE + \beta_6 \times DECK + \beta_7 \times POORROOF \quad \text{Eq. II-3} \\ + \beta_8 \times DIST - \text{TRAILS} + \beta_9 \times DIST - \text{GC} + \beta_{10} \\ \times DAMAGE + \beta_{11} \times RISK + \varepsilon \end{aligned}$$

Where P is the assessed value of the house, the βs are the estimable coefficients for each independent explanatory variable, and ε is the mean-zero error term. In terms of explanatory structural attributes of houses, a continuous variable is included for the area of the building in square meters ($AREA$). Dummy variables are included for multiple bathrooms ($2 + BATHS$), Garage Area ($GARAGEAREA$), construction quality ($HIQUALITY$). Also the existence of a fireplace ($FIREPLACE$), deck ($DECK$), and less fire-resistant roofing system ($POORROOF$) are included as dummy variables. In terms of neighborhood characteristics distance to the closest trail network ($DIST - TRAILS$) and distance to the municipal golf course ($DIST - GC$) are included.

In terms of wildfire attributes that affect housing market, as previously detailed, primary variables of interest are the view on wildfire burn scar as a measure of wildfire damage ($DAMAGE$), and the area of the land inside home ignition zone that bears canopy fire risk as the measure of wildfire risk ($RISK$). Note that our measure of damage is constructed as a continuous variable (visible area of burn scar) compared to prior work that only use dichotomous (view or no-view) measure. Additionally, our measure of risk is also a continuous variable constructed using multiple types of information including climate, topography, and fuel type.

In terms of wildfire damage and risk there are two distinct hypotheses of interest. First, under the null hypothesis, if there are no differences between homes with varying views on the Cerro Grande wildfire scar, then the estimated coefficient on the $DAMAGE$ variable would be zero ($H1_0$: $\beta_{11} = 0$). The alternative hypothesis is that if the assessed values of houses are negatively impacted by the view on wildfire scar, then:

$$H1_a: \beta_{11} < 0. \quad \text{Eq. II-4}$$

If the burn scar is associated with a negative disamenity, then the directional effect of this view of the damage is expected to be negative.

Second, under the null hypothesis that house values are not affected by the ex-ante wildfire risk, then the estimated coefficient on $RISK$ would be zero ($H2_0$: $\beta_{12} = 0$). Alternatively, if estimated wildfire risk negatively impacts house values, then the alternative hypothesis would be:

$$H2_a: \beta_{12} < 0. \quad \text{Eq. II-5}$$

We expect wildfire risk to negatively impact housing values. Perhaps the strongest signal to indicate social learning about wildfire risk in the community, would be for the evidence to support both H1a and H2a, simultaneously. That is, the behavioral trail of the damage event is still statistically present in the local housing market, and ex-ante risk is also being capitalized. Housing market signals would then be the clearest to support broader fire adaptation efforts in the community. However, adaptive social learning might be absent for a variety or combination of reasons: homeowners might feel that the federal government will act as the insurer of last resort (McKee et al. 2004), or be reliant/confident in suppression (Busby et al. 2013); and perceived risk preferences may differ from expert or objective assessments (Meldrum et al. 2015) and conflated by the correlation between some physical aspects (such as vegetation) and amenity value, swamping any negative risk signals (Donovan et al. 2007). Thus, the significance and directional effect of any ex-ante risk is ultimately an empirical question.

Without considering any spatial dependencies, equation 2 could be estimated via Ordinary Least Square (OLS) regression. However, the existence of spatial pattern in the error term should be investigated using Lagrange Multiplier (LM) test to ensure (see Mueller and Loomis (2008))

In the presence of spatial error, the error structure in equation 2 is specified as:

$$\varepsilon = \lambda WP + \mu \quad \text{Eq. II-6}$$

In this specification, λ is the estimated coefficient for the spatial error and W is a spatial weight matrix, P is the dependent price variable (or assessed housing value) and μ is a vector term of uncorrelated error terms. A spatial weight matrix indicates if two properties are neighbors. The size of the matrix is N by N, where N is the number of properties in the observations. Non-zero elements on each row signal the existence of a neighborhood relationship between the properties identified by the row and column indices. There are three criteria of determining the relevant neighborhood. First, the Inverse Distance criterion considers two properties as neighbors when the inverse of the distance between properties is less than a given cut-off point. A cutoff point of 2.8 km (1.75 mile) was selected using a trial and error approach and checking for the robustness of the results, as well as following Mueller and Loomis (2008). Additionally, as their names suggest, Four Nearest Neighbors (4NN) and Eight Nearest Neighbors (8NN) assign non-zero values to four and eight elements on each row for the four and eight nearest neighbors, respectively.

5. Results

Descriptive statistics of all variables used in the modeling (as defined in Table 1) are presented in Table II-2.

Table II-2: Descriptive Statistics (n=1,607)

Variable	Mean	S.D.	Min.	Max.
P	316,977	94,512	95,300	674,520
$AREA$	229	76	81	66
$2 + BATHS$	0.500	0.500	0	1.00
$GARAGEAREA$	29	27	0	204
$HIQUALITY$	0.5401	0.499	0	1
$FIREPLACE$	0.724	0.447	0	1
$DECK$	0.428	0.495	0	1
$POORROOF$	0.530	0.499	0	1
$DIST\_TRAILS$	600	3577	2.614	1743
$DIST\_GC$	2821	3248	0	14305
$DAMAGE$	2.521	2.796	0	96
$RISK$	271.624	835.67	0	8100

The final usable sample size is 1,607. In 2013 the average assessed house value was \$316,977 (2012 US dollars). The average area of a house is 229 m^2 (2,465 ft^2) with a garage area about 30 m^2 (320ft^2). Almost half of the houses have more than 2 bathrooms and more than half (54%) of houses rated of high quality. The majority of houses (72%) have a fireplace, 43% have a deck, and 53% of houses' roof systems have low to no resistance to outside fire's heat and flames. An average house is about 600 m away from a trail on the

Los Alamos mesa and the average distance to the golf course is 2,820 m. Finally, in terms of $DAMAGE$, on average, 2.5% (about 4.6 Km^2) of the Cerro Grande fire scar is visible from a house in Los Alamos and, in terms of RISK within ignition zone of an average house there is 276 m^2 area ranked as prone to crown fire.

Table II-3 presents the empirical results for the semi-log model in equation 2 using OLS regression (before accounting for the spatial error).

Table II-3: OLS Results (Dependent Variable = *ln* P; n=1,607)

Variable	Coefficient
CONSTANT	11.850443 (0.047156)***
$AREA$	0.002659 (0.000172)***
$2 + BATHS$	0.071442 (0.024992)***
$GARAGEAREA$	0.001313 (0.000387)***
$HIQUALITY$	0.181288 (0.022240)***
$FIREPLACE$	0.036153 (0.023017)***
$DECK$	0.008405 (0.021615)
$POORROOF$	-0.022918 (0.021109)***
$DIST\_TRAILS$	-0.000060 (0.00030)***

$DIST\_GC$	0.000014 (0.000004)***
$DAMAGE$	-0.017861 (0.007573)***
$RISK$	0.000016 (0.000013)***

Notes: Numbers in parentheses are standard errors. ***, **, and * indicate statistical significance at the 0.01, 0.05 and 0.10 levels, respectively

In terms of overall goodness of fit, the $\bar{R}^2$ is 0.86. As expected, the estimated coefficients on the variables $AREA$, $GARAGEAREA$, $FIREPLACE$, $2 + BATHS$ and $HIQUALITY$ indicate positive and significant impacts on housing values. While also positive in sign, the estimated coefficient on $DECK$ was not significantly different from zero. Also as expected, the estimated coefficient for $POORROOF$ variable is negative and significant, suggesting that less fire-resistant roofs (e.g, asphalt shingles and wood shakes and shingles) are not assessed as preferred roofing materials.

In terms of neighborhood variables, the estimated coefficient on $DIST - TRAILS$ is negative and significant, suggesting that houses further away from a trail have lower property values. Alternatively, we find that the opposite in terms of $DIST - GC$, where it is statistically significant and positive. While this is different than many standard, urban hedonic empirical estimates, perhaps the fact that these houses are in the WUI and the natural green area is readily available, might be the reason that closeness to the golf course is not necessarily an amenity.

We turn to the two primary hypotheses, and the estimated coefficients on damage and risk. The estimated coefficient on the wildfire damage variable $DAMAGE$ is negative and significant at the 0.01 level. Thus, the evidence supports the alternative hypothesis $H1_{a}$, that an increase in the view of the burn scar is associated with a decrease in property values, indicating a disamenity. In terms of ex-ante wildfire risk preferences, the estimated coefficient for the $RISK$ variable is positive and significantly different from zero at the 0.01 level. This is consistent with rejecting the null hypothesis, but the sign is in the opposite direction of the expectation; thus, the evidence does not support the alternative hypothesis H2. The positive sign on $RISK$ indicates that wildfire risk measure is not viewed as a negative attribute (i.e., wildfire risk is not being negatively capitalized into housing values). Thus, even though it is clear that wildfire damage is negatively associated with property values, and despite the use of a relatively sophisticated risk measure, the risk of wildfire does not negatively affect property values. This is seen even when the presence of less fire-resistant roofs is found to lower house prices, as has been found previously by Donovan et al (2007). While speculative without further information about preferences, this is perhaps in part due to the aesthetic or amenity value of vegetation swamping any negative risk effect (e.g., Donovan et al. 2007).

As noted previously, the concern with the OLS models is the failure to account for any possible spatial interdependency. Preliminary spatial tests, including both Maron's I and Lagrange Multiplier tests by Anselin (1988) indicate the presence of spatial lag and spatial error. However, as mentioned previously, the results of spatial lag model didn't converge and are not presented; here, only the results of Spatial Error

Model (SEM) is presented and discussed in Table II-4. Recall that three different SEM specifications are used for spatial weight matrixes (4NN, 8NN and Inverse Distance,).

Table II-4: SEM Results (Dependent variable=Ln P; n= 1,607)

Variable	4NN		8NN		Inverse Distance	
	Coefficient	z-probability	Coefficient	z-probability	Coefficient	z-probability
CONSTANT	11.929411	0.000000	11.942451	0.000000	11.982391	0.000000
$AREA$	0.002465	0.000000	0.002443	0.000000	0.002562	0.000000
$2+BATHS$	0.057723	0.000000	0.058429	0.000000	0.066870	0.000000
$GARAGEAREA$	0.000990	0.000000	0.000990	0.000000	0.001184	0.000000
$HIQUALITY$	0.170131	0.000000	0.169285	0.000000	0.177607	0.000000
$FIREPLACE$	0.022719	0.000068	0.024671	0.000035	0.032529	0.000001
$DECK$	0.004558	0.430928	0.008320	0.154691	0.012235	0.051812
$POORROOF$	-0.025055	0.000004	-0.025905	0.000010	-0.022265	0.000205
$DIST-TRAILS$	-0.000074	0.000000	-0.000080	0.000000	-0.000045	0.000000
$DIST-GC$	0.000013	0.000000	0.000009	0.000000	0.000010	0.000000
$DAMAGE$	-0.012092	0.000000	-0.009972	0.000000	-0.006863	0.020303
$RISK$	0.000012	0.000000	0.000013	0.000000	0.000014	0.000000
λ	0.501000	0.000000	0.632000	0.000000	0.990000	0.000000
$\bar{R}^2$	0.8886		0.8891		0.8745	
Log Likelihood	1790		1800		1747	

As shown in Table 4, in terms of goodness of fit, the $\bar{R}^2$ values for the SEM's are all in the narrow range of 0.88 to 0.89, and slightly higher than for the OLS regression. Log likelihood values are very similar for the three spatial models with a slightly higher value for the case of 8NN weighting matrix. In terms of the signs and significance of the estimated coefficients, the results from OLS remain essentially the same across all spatial econometric specifications. Again, the only variable with an estimated coefficient that is not statistically significantly different from zero is $DECK$. In addition, the coefficient of spatial error (λ), is significant at 0.01 level, with the estimated value between 0.5 (in the case of the 4NN), and 0.99 (in the case of Inverse Distance). In terms of our hypotheses of interest, for the SEM's the evidence continues to support hypothesis H1a, as wildfire damage is negatively related to housing values, and not support hypothesis H2a, as rather than negatively related wildfire risk is instead positively related to housing values; only in the case of Inverse Distance weight matrix the significance levels of the estimated coefficient drops from 0.01 to 0.05 level. But once again, we note that homeowners do not appear to be completely unaware of risk, as less fire-resistant roofs are shown to significantly lower house price.

Finally, Table II-5 presents the marginal implicit prices of housing attributes or characteristics, which are the partial derivatives of the hedonic price equation with respect to these characteristics (Taylor 2003).

Table II-5: Estimated Implicit Prices (2012 USD)

Variable	OLS	SEM (4NN)	SEM (8NN)	SEM (Inverse Distance)
$DAMAGE$: per percent of area of wildfire burn scar visible from the house's location (Calculated as $\beta_{10} \times \bar{P}$)	-5,662 5	-3,833 4	-3,161 4	-3,175 4

$RISK$: per area in square meters of crown fire risk-bearing land in 30 ft proximity of the building (Calculated as $\beta_{11} \times \bar{P}$)	

The focus is on our two primary wildfire characteristics: ex post $DAMAGE$ and ex-ante $RISK$. Specifically, the implicit price for a marginal change in housing attribute X is calculated in our semi-log model (e.g., see Mueller, Loomis, and Gonzalez-Caban 2009) as:

$$\partial \mathrm{P} / \partial \mathrm{X} = \beta_X . \bar{P} \quad \text{Eq. II-7}$$

Using OLS, the calculated negative impact of the view on fire scar is -$5,662 per percentage of burn scar visible. For the mean house in our Los Alamos sample this equates to $13,962, which is approximately 4.4%of the assessed housing value. For the spatial error models (SEM) the calculated negative impacts are all in a narrow band of $2,175 to $3,833 per percentage burn scar view; this equates to a value decrease of $5363 to $9,452 (in capitalized present value terms), or approximately 1.7 to 3% of the average assessed housing value, or 2.5 percent in case of the SEM model with 8NN weight matrix that has slightly better fit.

Using OLS, the calculated implicit price of the positive impact of the ex-ante $RISK$ measure is $5 per $m^2$of area in the risk-bearing ignition zone. For the mean house in our Los Alamos sample, this equates to a positive impact of $1,358 (in capitalized present value terms), which is approximately 0.4 percent of the assessed housing value.

Based on the SEM results, the equivalent positive impact for the mean house in our sample is $1,087, which is about 0.3% of the average assessed housing value.

6. Conclusions and Policy Implications

Using GIS tools for measuring spatial attributes of house locations as well as spatial econometric modeling, the objective of this analysis was to apply a hedonic pricing model (HPM) to decompose the impact of two attributes of wildfire on housing values in the Wildland Urban Interface (WUI): (i) a burn scar, representing the disamenity of a historical wildfire event; and (ii) the risk of a future wildfire event. The application was to an isolated WUI mountain community with historical experience with a high-severity, high damage wildfire event (Cerro Grande Fire of 2000). Viewed through the lens of social learning (Cutter et al. 2008), the housing market is investigated as a possible indicator of community adaptation or responsiveness to risk. If a community experiences a significant damage event, will it make them more sensitive or responsive to ex-ante risk, especially when the damage event is still highly salient with a visible burn scar?

Econometric results indicate that while over a decade has passed since the Cerro Grande Fire of 2000, the scarred landscape from this previous disaster still has a significant negative impact on the assessed value of houses. For the mean house in our sample, this negative effect represents approximately 2.5 percent of value. In contrast, the current threat of wildfire in the home ignition zone is not capitalized as a negative determinant of housing value, but rather has a small positive effect (approximately 0.3 percent of value for the average house). Of note, While significant effort was made to use a detailed risk measure, it is possible that an amenity or aesthetic value of the vegetation (one component of the Flammap assessment), is still predominating. Such a vegetation effect would be consistent with our finding that housing values do at least partially reflect risk, but only in terms of less fire-resistant roofs.

As with any case study, the caution is to be careful with generalizing. But, the failure of the Los Alamos housing market to fully capitalize wildfire risk is consistent with the wildfire risk mitigation paradox, where private landowners in the WUI undertake sub-optimal risk mitigation actions (Steelman 2006; Busby and Albers 2010). Specifically, our case study HPM results imply that the paradox is possible even when wildfire damage remains highly salient, and the community appears relatively well positioned to understand the risk of damage events. Certainly, many low-income forested communities in New Mexico and elsewhere will be less able to assess risk and afford mitigation. Speculatively, there are a variety of possible reasons for our case study, revealed preference results on the wildfire risk measure. In addition to a possible amenity value effect from trees and vegetation, there is or perhaps there is possible belief that the federal government may always act as the insurer of last resort. There is a need for continued theoretical (e.g., Busby et al. 2013) and survey research (e.g., Meldrum et al. 2015) to help disentangle these possible factors.

In the WUI decision environment of shared responsibility between public land managers and the private homeowners for a risk externality (Little et al. 2016), private market failure to respond to risk (e.g., decreasing value when ex-ante risk is increasing) raises the question of appropriate public intervention (and see Hjerpe et al., 2016). The key will be sorting through the type of interventions that are needed. We argue that the results of this analysis support: (i) continued investigation (e.g., Donovan et al., 2007; Mozumder et al. 2009; Prante et al. 2011; Meldrum et al. 2015) of whether improved information distribution about ex-ante risk can alter risk awareness and preferences in a WUI community; (ii) implementing incentives to increase homeowner risk mitigation, such as cost-sharing and mitigation-contingent insurance (Prante et al. 2011; Meldrum et al. 2014; CoreLogic 2015; Little et al. 2016); and (iii) exploring alternative institutional arrangements to help finance increased risk mitigation at regional landscape scales. With respect to the latter, such alternative institutional arrangements might specifically be tied to property/hazard insurance in the WUI. For example, recent 2015 NM legislative efforts included a proposal to divert a portion of property insurance tax revenues to a public mitigation fund to help increase the scale of wildfire risk mitigation efforts (HOUSE BILL 38, 52ND LEGISLATURE - STATE OF NEW MEXICO - FIRST SESSION, 2015). HB 38 was passed by the 2015 NM legislature, and then vetoed, by the governor. While to date unsuccessful, creating new institutional mechanisms to finance broader watershed restoration efforts will likely be a multi-year effort.

Finally, and more broadly, the social costs of high-severity, catastrophic wildfires clearly extend beyond the boundaries of the flame zone and impacted WUI areas, reaching downstream through the watershed and affected drinking water supplies (Adhikari et al. 2016), and across the airshed in the health impacts of wildfire smoke (Richardson et al.

2012; Jones et al. 2015). So, designing public financing mechanisms to pay for landscape-scale forest restoration efforts (a type of payment for ecosystem services (Adhikari et al. 2016)) will need to account for the full range of these beneficiaries. Yet, it is also clear that seeding social learning, and overcoming the wildfire risk mitigation paradox for private property owners in the WUI remains an important piece of the sustainability challenge. Fostering risk mitigation can help improve resilience and coping with future wildfire disturbances, slow the escalating public costs of suppression, and build more sustainable forest communities.

III. Optimal Wildfire Risk Mitigation for Residential Buildings in the Wildland Urban Interfaces: A Cost Estimation Framework

Abstract Communities near forests are vulnerable to wildfires. Retrofit measures to reduce vulnerability of residential buildings to wildfire include improvements to building's exterior, and within the parcel limit that hinder, mitigate, or prevent damage from wildfire heat and embers. The objective of this study is to provide a cost model for optimal retrofit planning for residential properties by integrating multi-attribute vulnerability rating systems, on-site wildfire vulnerability assessments, property characteristics and uncertainty in homeowner preferences. Integer programing is used to find optimal combination of retrofit activities that leads to the minimum total cost of vulnerability mitigation. The cost model is derived for wildfire retrofit planning for residential properties based on building's area and initial vulnerability rating of properties. The resulting cost model suggests that for an average property in study area, an extra unit of vulnerability measure adds 119 dollars to the minimum retrofit costs. The framework proposed in this study for deriving a vulnerability retrofit plan cost model in a WUI community can be used for other types of natural hazards and in other communities.

Keywords: Vulnerability Assessment, Mitigation, Multi-Attribute Rating System, Retrofit Measures, retrofit plan, Integer Programming, Wildland Urban Interface, Monte Carlo Simulation, Wildfire, Natural Hazards

1. Introduction

Wildfire is an increasing threat in the United States as well as in many other parts of the world. Wildland Urban Interfaces (WUIs), where urban areas and forestlands interdigitate, are wildfire risk zones (Radeloff et al. 2005), where properties and assets are in danger of burning due to wildfire. While changes in temperature and precipitation are perceived to result in an increase in the number and intensity of wildfires (Benkert-Smith et al. 2015), expansion of the WUI areas increase the exposure of communities to wildfire hazard. There are approximately 770,000 km^2 WUI area in the United States, including 44 million homes that accommodate 99 million people (Martinez et al. 2015). Theobald and Romme (2007) estimated that 90% of the WUI area in the United States is categorized as high severity forest fire regimes. Between 2006 and 2015, the annual loss to wildfire ranged between 200 million dollars (in 2014) to 4 billion dollars (in 2007) (Insurance Information Institute 2016). However, the actual vulnerability of the residential buildings to wildfires are estimated to be much higher than past statistics (Alexandria et al. 2016; Insurance Information Institute 2016).

Protection of people and properties in WUIs is facilitated through strict laws and regulations for new developments in the WUIs as well as fostering residential retrofit measures that make private properties “wildfire resistant”. Residential retrofit measures that can be implemented to mitigate wildfire hazard include both structural and non-structural changes to the property. Nonstructural retrofit measures are mainly removing and rearranging potential wildfire fuel from the Home Ignition Zone (HIZ) (Cohen 2000;

Beverly et al. 2010). HIZ is the building and its surroundings within 30 to 60 meters from the home, where fire can reach to the building through radiation, convection, or flying embers (Cohen 2004; Beverly et al. 2010, Quarles et al. 2010). Trees, shrubs, grass and other vegetation within HIZ can be consumed by a nearby wildfire and become wildfire fuel and burning flames themselves. Structural retrofit measures for wildfire mitigation are all connected to building's exterior and are so as to avoid fire penetrating the interior (Cohen 2001). Structural retrofit measures include re-roofing of low to now fire-resistance roof systems, covering external walls with fire-resistance material, covering open foundations, etc. A study by Cohen (2000) showed that a vegetation clearance of 10 to 20 meters from the buildings with fire resistant roofing can reduce the structural ignition due to outdoor fires up to 90%.

Despite its salient impact on reducing the homeowner loss to wildfire, homeowners have a tendency to under-invest for retrofit measures that mitigate their vulnerability to wildfire (Little et al. 2015, Steelman 2008, Busby and Arbor 2010). This fact is attributed to the spatial externalities of wildfire risk management and the reliance of homeowners on suppression capabilities of forest managers and the mitigation of hazardous fuel on the adjacent forests (Busby and Arbors 2010; Olmstead et al. 2012; Gude et al. 2013).

The objective of this paper is to find the minimum-cost retrofit plans for several residential properties that satisfy the condition of reducing vulnerability below an acceptable level of vulnerability. Two main benefits are sought by addressing this problem: (1) finding an optimal investment cost estimate for mitigating homeowner's vulnerability to wildfire, which is tangible for an average homeowner, and (2) to propose a cost estimation framework that includes steps for data collection and handling to finding optimal retrofit measures for a large number of homes in a natural hazard prone area. The proposed framework uses the records of properties whose vulnerabilities to wildfire are numerically estimated using a Multi-Attribute Rating System (MARS). Thereafter, the cost-estimation module identifies unit and total costs of implementing each retrofit measure for each and every property in the study area. The minimum-cost retrofit plan is found by utilizing an integer programming optimization method. Furthermore, the generated minimum cost data is used to derive a mitigation cost model for the WUI community under study.

2. Background

The National Fire Protection Agency (NFPA) code 551 (NFPA 2016) indicates Cost estimation of buildings' fire safety measures as one of the needs of homeowners as well as other stakeholders (i.e. "*any individual, group, or organization that might affect, be affected, or perceive itself to be affected by the [fire] risk"* (NFPA 2016)) that should be addressed in any fire risk assessment process. Clarification of vulnerability factors in cost estimations and level of acceptable vulnerability are indicated as important characteristics of a cost-benefit analysis by NFPA. Hence, the first step in cost estimation is defining vulnerability. Vulnerability is defined as the degree of harm a system is likely to experience due to exposure to a hazard (Turner II et al. 2003) and can be assessed both quantitatively and qualitatively. A quantitative way to determine structural vulnerability to natural hazards is through designing damage or fragility curves. Fragility curves are designed for various hazards such as earthquakes, hurricanes, and indoor fires (Unnikrishnan and Barbato 2015; Li and Lindt 2012; Gernay et al. 2016). For wildfires, Cohen (1995) designed a Structural Ignition Assessment Model (SIAM) that returns the probability of ignition of a building element due to the heat from an outdoor fire and the arrangement of the fuel in the surroundings of the building. SIAM does not predict structural survival or modes of failure, but estimates the probability of ignition of exterior building elements, which can facilitate penetration of fire to the interior of the building.

Although quantitative methods are accurate and can capture small changes in vulnerability, these methods are usually computation-intensive (Watts 2016). A consequence of this resource demanding nature of such computations is that the results usually pertain to a small number of buildings. Hence, the estimated cost data for retrofit plans based on quantitative methods are very sparse. Stockmann et al. (2010) analyzed retrofit options for 252 homes in Bitterroot Valley, Montana using the SIAM model. They investigated cost effectiveness of a variety of retrofit measures including replacement of the windows, changing flammable siding to non-flammable siding, changes to the landscaping, complete change of the vegetation type in the HIZ, and some combinations of these measures. In order to find the impact of each alternative in reducing vulnerability, they modeled all properties in SIAM software and estimated the ex-ante probability of burn for different mitigation measures. As for the effectiveness of the measures taken for each property, they found that removing and replacing the vegetation and fuel inside the HIZ is the most effective measure to reduce the probability of ignition. They estimated a total cost of $11,288 per home to decrease the ignition probability from 0.00484 to 0.00179.

Studies have shown that homeowner's sense of self-efficacy regarding wildfire risk mitigation to be among the top drivers of homeowner's willingness to investment on implementing such measures (Martin et al. 2009). Probabilistic expressions of the mitigation effectiveness is of interest to experts; however, a small probability is not comprehensible for a lay person (Sjoberg 1999), and hence, may fail to motivate adoption of mitigation plans. A qualitative alternative for assessment of vulnerability and effectiveness of retrofit measures is the multi-attribute rating or vulnerability indexing. For example, Lagomarsino and Gionivazzi (2006) suggested a multi-attribute scheme for estimation of vulnerability of buildings to earthquakes, and argued that this approach is generalized over different areas with seismic hazard with less difficulty compared to quantitative methods. Kappes et al. (2012) proposed a multi-attribute, multi-hazard vulnerability rating schedule that qualitatively rated buildings for rock fall, flood, shallow landslides, debris flow, and flash floods for mapping community vulnerability. The optimal costs of retrofit measures regarding indoor fire safety has been previously investigated using multi-attribute rating systems (MARS) for vulnerability assessment (Watts 2016). MARS requires less computing resource investment compared to its exact equivalents and can be used in the estimation of the retrofit costs for a large number of buildings. There are a few MARSs available for the assessment of residential buildings' vulnerability to wildfire in WUI areas, namely Appendix C of the Internarial Code Council (ICC 2015), the MARS proposed as a part of the North East Decision Model (NED) (Twery et al. 2012), and MARSs designed for specific WUI communities.

In the presence of historical and survey data, a cost estimation model can be formulated using regression analysis (Jafarzadeh et al. 2015; Jafarzadeh et al. 2014). However, such models are descriptive in nature and do not prescribe the optimal retrofit plan. In other words, in such models the retrofit solutions are known a priori, compared to retrofit plans that are deducted from optimization models (Asadi et al. 2014). The optimization of retrofit measures for hazard mitigation is more popular for infrastructures such as bridges (Chandrasekaran & Banergee 2015; Mondoro et al. 2016), surface water conveyance systems (Diaz-Nieto, Lerner, & Saul 2015), and highway network (Fan et al. 2009). Variety in design, size, and materials used in construction of residential buildings make it difficult to derive optimal retrofit plans for several buildings in an urban scale. One of the large scale models for optimization of the cost of residential buildings' retrofit plans is proposed by Delmastro, Mutani, and Gorgnati (2016) with the energy consumption retrofit target. Their model combines GIS data and energy audits to select a retrofit plan for each building from a mix of cost-optimal retrofit packages based on the building type and a socio-economic feasibility measure. The procedure is to cluster buildings into reference building types and deducting the cost-optimal retrofit plan for the reference buildings. Although this model is suitable for large scale decision making and also mapping the optimal retrofit plans, it does not provide a cost model related to the energy savings as the retrofit target, or the physical characteristics of the reference buildings. Such aggregation doesn't allow for tailoring optimal retrofit plans for each property in the study area.

This study utilizes a locally designed MARS for wildfire vulnerability assessment to estimate and compare the costs of retrofit plans for residential buildings. Applicable retrofit measures are inferred from the individual properties' evaluation card on an automatic basis. A "moderate" rating is selected as the cutting point for acceptable level of vulnerability and, accordingly, the optimal plan for mitigating high and very high vulnerability buildings to moderate rating level is estimated as the optimization constraint. The optimization objective is to find the combination of retrofit measures that result in the minimum implementation cost while satisfying post-retrofit vulnerability level constraint. A Monte Carlo sampler is used to draw unit cost of retrofit measures from its associated PERT cost distribution. Hence, rather than a unique number, a range of costs of optimal retrofit plan is found for each property. The contribution of this study is to provide optimal retrofit plan for residential properties at a large scale (more than 300 buildings) and with the retrofit goal of reducing vulnerability to wildfire. The study also provides an optimal-cost model for retrofit planning of properties in a given urban area.

3. Methodology

The proposed framework is shown in Figure III-1. The framework integrates four sources of data: (1) MARS data, (2) vulnerability assessment data, (3) property characteristics, and (4) cost data.

Figure III-1: Framework for Large Scale Optimal Retrofit Planning

MARS is used as the basis for determining retrofit measures and their effectiveness in terms of reducing vulnerability to wildfire. A part of every MARS designed for wildfire vulnerability assessments is allocated to the conditions of the surroundings of the building and inside the HIZ, such as trees, ground cover, and fuel connection, among others. Another part considers the building elements and materials on the structure's exterior such as the roofing material, coverage of the foundation, exterior wall, among others. For each one of the aforementioned attributes, possible modes are defined - each mode is a group of materials or design alternatives of an attribute that responds to wildfire heat and flames in a similar way (e.g. fire resistance, flammability, combustibility, or conductivity). The vulnerability rating of each mode is also indicated in MARSs, the higher the vulnerability rating assigned to a mode, the more vulnerable is that mode to wildfire heat and flames. For example, the attribute of “exterior walls” is assigned two modes in a MARS, the modes are namely, “brick, stone or metal” and “vinyl or wood”, with a vulnerability rating of zero and five, respectively, in that, the having a vinyl or wood exterior wall adds 5 units of vulnerability to the overall vulnerability of the property.

Site visits are necessary to assess the total vulnerability of each property as the sum of vulnerability ratings of all attributes of the parcel indicated in MARS. Site visits are usually undertaken by fire fighters, or agents from insurance companies. A vulnerability evaluation card is completed on the site of each property. During site visits, the mode associated with each and every attribute on the evaluation card is matched with existing condition of property and the rating for each attribute (such as exterior wall, roofing material, foundation, etc.) is marked on the evaluation card. The total vulnerability rating of a property is then calculated as the sum of the ratings assigned to all of the attributes. This total vulnerability rating is then compared with a predefined scale to determine the qualitative vulnerability rating of the property (e.g. low, medium, high, very high, and extreme).The vulnerability assessment database stores addresses and evaluation cards of the assessed properties.

The set of feasible retrofit measures for each property are derived from the property’s evaluation card. Retrofit measures are possible changes in the modes of the attributes that result in a lower vulnerability rating of an attribute and therefore decreases the total vulnerability rating of the property. Thus, any attribute whose mode matches with the minimum possible rating, as indicated on the evaluation card, will be excluded from the potential retrofit plans. Since, in MARS, the attributes are assumed to be independent from each other, each retrofit measure relates to reducing the rating of one and only one attribute. Consequently, for each property, a set of retrofit measures along with their impact on the vulnerability rating reduction can be determined. When the homeowner decides to implement retrofit on an attribute to reduce vulnerability to wildfire, his selection will be to retrofit so that the mode has a post-retrofit vulnerability rating of zero. The assumption made here is that in order to make each retrofit measure's investment economically the most effective, homeowner will choose to target achieving the most vulnerability mitigation amount by arriving at the least vulnerable post-retrofit condition of the retrofit subject (i.e. structural or land element).

For each set of retrofit measures for a single property, the overall cost of mitigation is obtained as the sum of the costs of implementing retrofit measures that are in the feasible retrofit plan. The costs of retrofit measure are drawn from a range of possible costs resulting from changing the mode of attributes to the least vulnerable mode. The amount of work required to implement each retrofit measure is estimated based on the building and parcel's plan design. The building's plan or the direct measure of the amount of work associated with each retrofit measure can be found in the property characteristics dataset that is recorded and kept by most of the counties' tax assessors' offices, and is treated as public information. Total cost is calculated by multiplying the unit cost of retrofit measure by the quantity of the associated work. For example, replacing the external wall's siding from vinyl to stone requires total length and height of the wall. The perimeter of the dwelling estimated from the building's plans is equivalent to the length of the wall, and the number and height of the stories can be used to calculate the height of the wall.

Integer programming is then applied to find the optimal retrofit plan. Acceptable vulnerability level, set of the feasible retrofit options, cost of implementing retrofit measures and the associated change in the total vulnerability rating are fed into an integer programming model to find the optimal retrofit plan, that yields minimum cost while ensures the vulnerability rating falling below the acceptable vulnerability level. The cost minimization objective is defined as follows:

$$C_i^* = \min_{x_{pi}}(\sum_{p=1}^{n_i} c_{pi}.x_{pi}) \qquad \text{Eq. III-1}$$

Where i denotes the property's ID, C_i^* is the minimum cost of the retrofit plan for property i, p is the index for the property attribute, x_{pi} is the optimization decision variable, which is a binary variable defined as:

$$x_{pi} = \begin{cases} 1 & if\ property\ attribute\ p\ is\ subject\ to\ retrofitting \\ 0 & otherwise \end{cases} \qquad \text{Eq. III-2}$$

, and c_{pi} is the total cost of applying retrofit measure on property attribute p in the i^{th} property, which is estimated as the amount of work times the unit cost of implementing the retrofit measure. The unit cost was estimated from the RS Means 2014, the National Renovation and Insurance Repair Estimator (2016), and bids submitted by local land treatment contractors to Taos County Soil and Water Conservation District (TSWCD). The total number of property attributes that can be retrofitted for reduction of vulnerability to wildfire is n_i. The constraint of the optimization is that the total rating of the property falls below the accepted level R^t from the initial total rating R_i^0:

$$s.t. \qquad \sum_{p=1}^{n_i} \mathrm{r}_{pi} \,.\, \left(1 - x_{pi}\right) \geq R_i^0 - \mathrm{R}^t \qquad \text{Eq. III-3}$$

Multiple values are available for the cost of implementing retrofit measure for each attribute. This is due to the fact that what is revealed to the modeler is the "group of modes" that building attribute's present conditions belong to. In other words, the exact mode of the property attribute, for present condition is not known to the modeler; in addition, the preferences of the homeowner for the post-retrofit mode is unknown, whereas the group of target modes are known to the modeler. To address these uncertainties, c_{pi} is modeled as a stochastic variable sampled from a PERT distribution. A Monte Carlo approach is used to sample from a possible range of costs of implementing each retrofit measure. The flowchart of the model combining integer programming and Monte Carlo sampling for N_i properties is shown in Figure III-2.

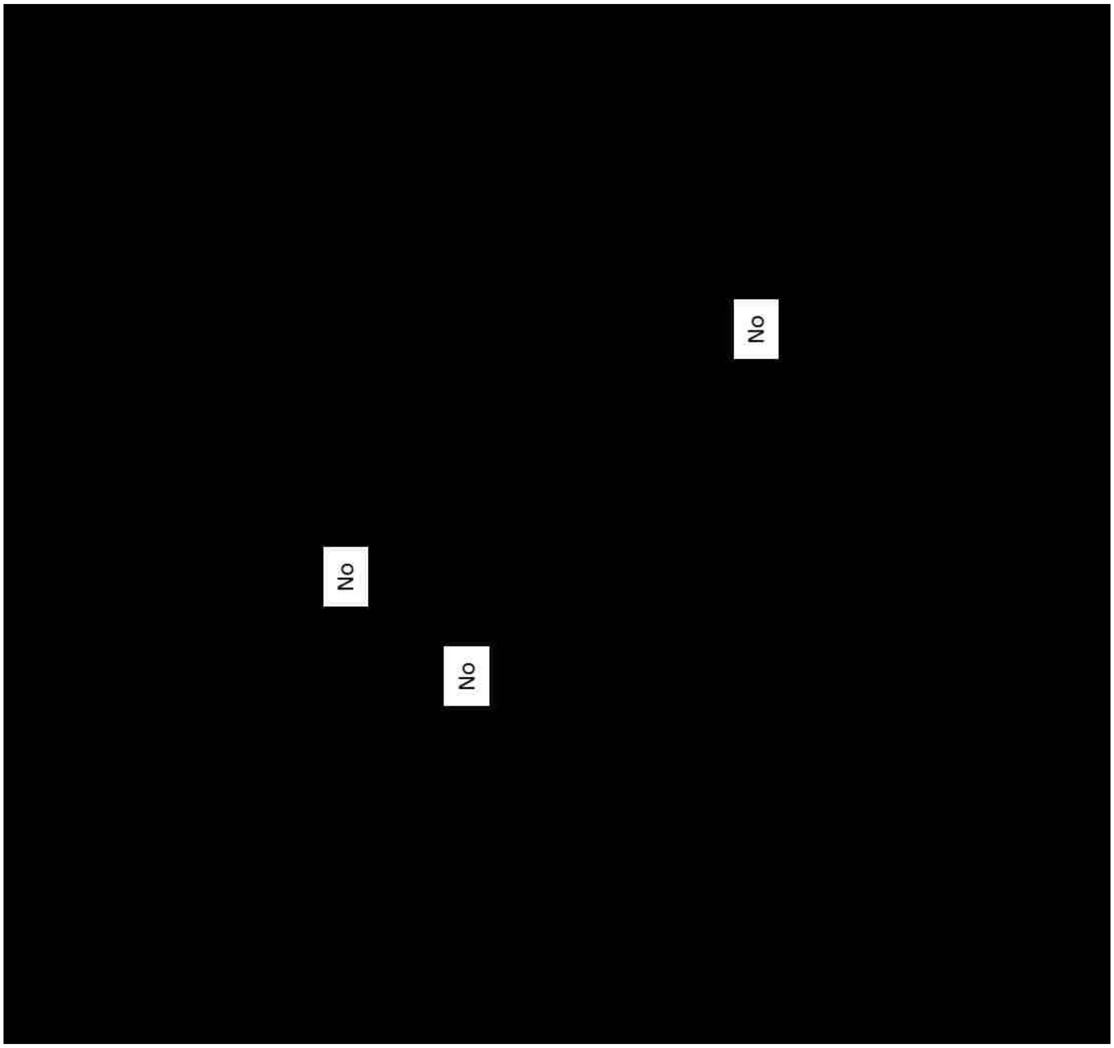

Figure III-2: Coupled Monte Carlo – Integer Programming Optimization for finding optimal retrofit plan for a large number of homes in a WUI community

The result of the framework shown in Figure III-2 is a prescriptive optimal retrofitting plan for each property given the cost contingencies, as well as the total cost of the optimal retrofit plan. The total costs of the retrofit plan is then derived as a function of the initial vulnerability rating (R^0) and the building are (A) using the output of the large-scale optimization module shown in Fig.1.

4. Case Study and Data Collection

The proposed framework is demonstrated using data from properties in Santa Fe, New Mexico, where a total of 19 neighborhoods have been subject to property vulnerability assessments by Santa Fe Fire Department (SFFD). Since 2008, several properties have been assessed, and some reassessed, based on Santa Fe's local MARS.

4.1. Vulnerability Assessment

The purpose of this property-by-property assessments by wildland section of the SFFD was twofold: to educate homeowners about their exposure to potential wildfires, and to provide spatial information for emergency management in the case of a wildfire (Evans et al. 2015). To assess a property's vulnerability to wildfire, the building structure, parcel's land, and the neighborhood are inspected. The vulnerability was assessed in two formats, a numerical scale between 0 and 185, 185 being the maximum vulnerability to wildfire, and a descriptive scale, from low to extreme vulnerability with each description covering an exclusive range of total vulnerability ratings. Low vulnerability class is assigned to properties with total vulnerability rating less than 30, total vulnerability rating of 60 divides moderate and high vulnerability class, and total vulnerability rating is the breakpoint between high and very high vulnerability class. Rarely, a property has a vulnerability rating of above 120, but in that case the property will be considered in an extreme vulnerability class.

To test the proposed framework, a total of 601 property assessment cards were obtained from the website of the SFFD. As shown in Table III-1, the assessment cards have four sections namely site hazard rating, structural hazard rating, hazard reduction factors and Community Wildfire Protection Plan (CWPP) rating.

Table III-1: Santa Fe's MARS: attributes, modes and ratings (Evans et al. 2015)

Section	Property Attribute identifier	Parcel Attribute	Modes	Mode Ratings
Site Hazard Rating	--	Driveway Length & Turnaround	Less than 46 m	0
			More than 46 m without adequate turnaround	3
			More than 46 m with adequate turnaround	5
	--	Driveway Width	More than 3.6 m.	0
			Less than 3.6 m.	5
	--	Driveway Obstruction	No overhead branches below 4.3 m.	0
			Obstructing overhead branches below 4.3 m	5
	--	Access Smoothness	No bridges/bridges with no restrictions	0
			Inadequate surface bridges for emergency vehicle	5
	--	Road Grade	Level or less than 10%	0
			Over 11%	5
	p_1	Gate	No gate / non-locking gate	0
			Locked gate restricting access	5
	--	Address Visibility	Visible from road (on house/end of drive)	0
			Not visible from road or not found	5

Section	Property Attribute identifier	Parcel Attribute	Modes	Mode Ratings
	p_2	HIZ Trees	No trees within 10 m from the building	0
			Hardwoods (with deciduous leaves)	4
			Mixed (hardwoods and conifers/evergreens)	7
			Conifers / Evergreens (non-deciduous)	10
	p_3	Ladder Fuels [b]	Include low limbs underbrush, vines, etc.	
			No	0
			Yes	5
	p_4	Fuel Connection [c]	Include ornamental shrubs, leaves, grass, weeds, mulch beds, etc.	
			No	0
			Yes	5
	p_5	Ground Cover	Sand, gravel, etc. (non-combustible)	0
			Grasses, up to 15.24 cm tall	3
			Grasses over 15.24 cm tall (heavy weeds, etc.)	10
			Herbaceous understory or forest leaf litter	15
			Shrubs with leaves	5
			Shrubs with needles (spreading juniper, etc.)	7
	--	Slope	Gradual (0%-10%)	0
			Moderate (11%-30%)	5
			Steep (over 30%)	10
	p_6	Combustibles	Include firewood piles, brush piles, stored lumber, outdoor furniture, etc.	
			None	0
			More than 10 meters from home	1
			1-10 m from home	5
			0-1 m from home	10

Section	Property Attribute identifier	Parcel Attribute	Modes	Mode Ratings
	p_7	Flammables	Include gas cans, gas grills, lawnmowers, pesticides, etc. None/Unknown More than 10 m from home 1-10 m from home 0-1 m from home	0 1 5 10
	p_8	Hazardous Materials	Within 10 m of the structure No Yeas	0 5
	p_9	Roofing	Metal, Slate, Tile or Class A Shingles Rolled roofing or non-rated roof material Wood (cedar shingles or shakes)	0 5 15
	p_{10}	Foundation	Enclosed (fireproof i.e.: concrete, metal, adobe) Enclosed with wood or vinyl sheeting Open air foundation (piers, stilts, etc.)	0 5 15
	p_{11}	Exterior Walls	Brick, Stone or Metal Vinyl or Wood	0 5
Structural Hazard Rating	p_{12}	Vents and Eaves	Enclosed with plastic or metal screens Exposed wood, open soffits or unscreened vents	0 5
	p_{13}	Attachments	Includes decks, overhangs, fenced, trellises, etc. No Yes	0 5
	p_{14}	Fuel traps [g]	Include window wells, under steps, foundation indents, etc. No Yes	0 5

Section	Property Attribute identifier	Parcel Attribute	Modes	Mode Ratings
Site Reduction Factors	--	Vulnerability reduction factors	Ladder fuels removed within 10 m of house	-1
			Grass mowed/water within 10 m of house	-1
			Leaves/needles raked within 10 m of house	-2
			10 m of gravel or non-flammable materials around house	-3
				-1
	--	Structural factors	Regularly cleaned roof and gutters	-1
			Deck skirting non-flammable/screened	-3
	--	Other	Firefighting equipment available (hose, ladders, etc.)	-1
			Usable water supply nearby (pool, pond, hydrant, etc.)	-3
CWPP	--	CWPP Neighborhood Rating	Low	0
			Moderate	10
			High	20
			Very High	30
			Extreme	35

Altogether, the assessment card has 25 attributes to be rated by the agent. The site hazard rating divides the parcel's land into less than 1 meter from the building perimeters, more than 1 meter but less than 10 meters, and road access area. The maximum rating that could be assigned to this section of the evaluation card is 105.

The structural hazard section included questions about the exterior materials and structural systems of the property. Roofing, foundation, exterior walls, vents, attachments, and possible fuel traps were assessed to evaluate the resistance of building materials and to detect possible wildfire fuel around the buildings' exterior. The maximum rating for the structural hazard section is 45. Hazard reduction factors include annual maintenance tasks such as pruning, and grass mowing. In addition to the availability of fire suppression equipment for fire fighters, the hazard reduction factors could reduce the rating by up to 15 units. CWPP rating is the rating assigned to the neighborhood by local CWPP committee. The neighborhoods in Santa Fe's WUI area received ratings (0, 10, 20, 30, or 35) based on their location with respect to the forest lands (Santa Fe National Forest) and their spatial characteristics such as slope, aspect, and overall vegetation cover. In this study, it is assumed that the homeowner has no control over this rating section.

4.2. Cost Estimation

Santa Fe County's assessor provides two formats of online data that can be used for estimating the amount of work for implementing retrofit measures, namely, the design plan of the buildings located on the property, and the tabular data. To estimate the costs of the retrofit plans, the pre-retrofit or as-is conditions of the structures are retrieved by backtracking from the vulnerability assessment evaluation cards. As shown in Table 1, each mode contains multiple types; for example, if the roofing system has received a rating of 5, from Table 1 it can be inferred that the roofing system at the time of the assessments had either rolled roofing or non-rated roof material types. In cases where the actual material or system of the property's pre-retrofit attribute is not known, all possible modes in the marked mode group are considered in the cost scenario. In the prior example of the roofing material, for the as-is condition, rolled roofing and all types of non-rated roof systems are accounted for as potential pre-retrofit scenarios.

As previously mentioned, the result of implementing retrofit measures on an attribute is a zero vulnerability rating for that attribute. In the previous example of the roofing system, the binary assumption for the retrofit measure dictates that the post-retrofit mode of the roofing system will be one of Metal, Slate, Tile or Class A shingles types as those are associated with zero rating for the roof system. The effectiveness of each retrofit measure is quantified as the difference between the original rating and the minimum rating of the attribute, but there is uncertainty in the costs of implementing each measure; in fact, the less is known about the physical characteristics of the buildings' exterior and parcel, the wider becomes the range of possible costs assigned to the implementation of the associated retrofit measure. Another important note is that after considering all the characteristics, and utilizing the available data to set up the potential retrofit plans, 11 attributes out of 25 were dropped from possible retrofit options either due to impracticality (e.g. changing the road grade level) or due to lack of data required for estimating the amount of work required (e.g. obstructing overhead branches). Those items have not received a variable name in Table 1 since they are not presented in the optimization model. For the remaining 14 attributes, the estimation of the unit cost of potential retrofit measures and assumptions are explained as follows:

- *Gate,* if locked, can block the firefighter's access to the property in case of a wildfire arrival to the property. To reduce the vulnerability associated with this item, the lock should be removed. The costs associated with this item is to remove the gate's lock to provide easier access for fire fighters, this cost is estimated per unit of length (m) using National Renovation & Insurance Repair Estimator 2016, which, hereafter, is referred to as National Estimator.

- *HIZ trees* located within 10 m from the building may expose the building to a great hazard when wildfire is torching. Burning parts of the branches detached from the tree can be easily carried by wind and land on the roof, causing roof ignition. In order to remove this hazard, ideally, the 10-meter buffer area around the house should be cleared of trees. If a rating greater than zero (4, 7, or 10) was assigned to this item in the vulnerability card, it implies that there is at least one tree in the 10-meter vicinity of homes. The number, type, and diameter of the trees are not identified to calculate the exact cost of clearing. The number of trees is generated between 1 and the maximum number of trees that can be accommodated within a 10-meter buffer ring around the structure. To calculated this maximum number, the average basal area of trees on the forest land is used as follows:

$$T = \frac{A_{10}}{\bar{B}} \quad \text{Eq. III-4}$$

- Where, T is the maximum number of trees, A_{10} is the area of the buffer around and within 10-meter of the building, and $\bar{B}$ is the average basal area of trees in the local forest. For trees in the Santa Fe National Forest, the average basal area is estimated at 2.3E-5 m^2 , after unit conversion (Lambert 2004). In case of availability of aerial photos for the properties, when the count of trees from the aerial photo is available, the minimum value of the count and T is used as the basis for cost estimation. The cost of removal of trees is calculated per tree (Ea.) based on the RS Means 2014.

- Ladder fuels are small trees and shrubs and medium height vegetation that provide continuity between surface fuel and tree crown or stand canopy (Peterson, et al. 2003). In order to remove the dormant vulnerability in ladder fuel, the trees should be pruned and spaced correctly, and the brush should be removed. The cost of removing ladder fuel is assumed at most the sum of the costs of thinning, cutting & piling dead and down limbs, and pruning per unit area (m^2). Data for this cost estimation is collected from bids submitted by local land work contractors TSWCD.

- Ground cover (e.g. grass, shrub, and herbaceous understory) in the HIZ can convey fire over the surface to building parts and attachments that are close to the ground. The most non-conductive forms of ground cover are gravel and sand, which is preferred from a vulnerability standpoint. The area of ground within 1 to 10 meters buffer of the dwelling is used to calculate the total cost of changing the ground cover. The unit cost is retrieved from the RS Means 2014.

- Fuel connection is also vegetation cover that connects building to the ground cover and if removed, reduces the probability of structural ignition due to ground fire. The connecting area is assumed to be within 1-meter distance from the building, and the unit cost is similar to the unit cost of changing the ground cover.

- Combustibles, as defined in the evaluation card, are outdoor furniture as well as wood or brush piles, or stored lumber. The ideal is to remove these combustibles, or to move them beyond the 10-meter buffer zone of the building structure. If the combustibles are mobile, it is assumed that there is no cost for moving them further away from the building. The maximum cost of clearing the 10-meter buffer area from the combustibles is assumed to be that of removing a wood storage shed. The range of costs for this item pertains to removing different shed sizes that are obtained from the national estimator per shed (Ea.).

- Flammables are similar to combustibles, but more specifically include flammable gas containers in the 10-meter buffer of the building structure. It is assumed that flammables can be moved away from the building at no cost.

- Hazardous materials not counted along with Combustibles and Flammables should be removed from the 10-meter buffer area. Removing hazardous materials is also assumed to come at no cost.

- Roof material is one of the most influential elements in the wildfire vulnerability rating of the structure. Roof is the target of flying ember because of its large flat area. For houses with rolled roofing, non-rated roof material, wood shakes and shingles there is a probability that embers will burn the roof and penetrate the building. Whereas replacing rolled roofs or non-rated roof systems with metal roof decreases the total vulnerability score by 5 points, and replacing wood roofs with metal, slate, tiles, or class A fire resistant roof systems reduces the vulnerability significantly by 15 points. According to ASTM E108, Class A roofing system has non-combustible deck material such as steel, poured gypsum, or concrete, etc. The costs of re-roofing are assumed to include removing the previous roof (Rolled , and unrated in case of rating of 5, and wood shakes and shingles in case of rating of 15), and replace it with a fire resistant roofing system (metal, slate, tile, and Class A shingles). Due to variety in replacement options a range of prices are provided based on the costs of different materials. The unit cost of replacement per unit area is retrieved from the National Estimator. The total cost of roofing is calculated as the area (m^2) of the dwelling plan multiply by the unit cost of the new roofing system.

- Foundation is not exposed to embers, but surface fires that can reach to the foundation skirting can burn the structure from beneath. To avoid this, foundations should be enclosed by fire resistant material such as metal or concrete. To retrofit foundation for wildfire proofing, the costs for replacing wood/vinyl covered foundation skirting (rating of 5), include both removal of the previous siding and replacing with fire resistant siding, whereas for open air foundation (rating of 15), the cost involves only placement of new siding.

- External walls are also exposed to wildfire flames, and can resist fire better if made of brick, stone, or metal. The costs of external wall retrofit pertains to replacing the siding by one of the brick, stone, and concrete materials. To get the area of the siding, the perimeter of the dwelling and the height of the dwelling building are used.

- Vents & eaves, if not enclosed, serve as an open window letting embers and flames to the interior space of the building. To block this opening from potential embers, the retrofit measure is to cover the opening using a screen. The cost of adding a screen is calculated per vent. The total cost is multiplied by the number of vents. In the absence of data on the number of vents, by rule of thumb is a vent per 14 (m^2) of the roof area.

- Attachments could include decks, overhangs, and fences among others. These create an extra contact area to fire flames and embers, and hence fire proofing or removing these attachments can reduce the vulnerability to wildfire. The area of the wood deck is specified in the characteristics collected by the tax assessment officials. If the presence of wood deck is specified, cost of removing or covering deck with fire resistant tiles are accounted for in the unit cost distribution.
- Fuel traps include any opening such as window wells and under-steps that contribute to the vulnerability of the building structure to wildfire flames and embers. For a property whose evaluation card indicates the existence of such traps, the maximum cost is assumed equivalent to the cost of enclosing an area of 0.3 (m) width and length which is equivalent to the perimeter of the building, and the minimum cost is assumed to be the cost of enclosing 0.1 m^2 area.

5. Analysis of Results

The number of parcels rated high vulnerability level using this study's MARS was 372, while the number of parcels rated with very high vulnerability was 229. After geo-coding (i.e., matching the property addresses on the MARS with the ones available in the county's assessor's interactive map) properties in order to get the quantity take-offs and cost estimates, the number of high vulnerability homes was reduced to 258 and the number of very high vulnerability homes was reduced to 131. In the case study, 12% of properties were rated by the SFFD with moderate vulnerability, 55% with high vulnerability, and 32% with very high vulnerability. Table 2 shows the estimated marginal and fixed costs of implementing each retrofit measure. Fixed costs are defined as the minimum starting costs for implementing each retrofit measure and are also retrieved from the National Estimator. The quantity of work for implementing possible retrofit measures, is estimated using the available plan views and tabular data of the buildings, as well as the aerial photo of the parcels, which are available in the Santa Fe's County assessor website. In addition, some of the retrofit measures are feasible for a larger number of properties than other measures. Column (5) and (6) in Table 2 present the percentage of properties rated with high vulnerability and very high vulnerability that could benefit from each retrofit measure. The average amount of work related to each retrofit measure in the study area is shown in column (7) of Table III-2.

Table III-2: Wildfire vulnerability retrofit measures, cost, percentage of homes in which the measures can be implemented for wildfire vulnerability mitigation objective, and average amount of work in the study area

Attribute Identifier (1)	Description (2)	Unit Cost [USD] {min, mean, max} (3)	Fixed Cost [USD] (4)	High Vulnerability Homes (%) (5)	Very high Vulnerability Homes (%) (6)	Average Quantity to Retrofit (unit) (7)
P_1	Remove driveway gate/gate lock	{9.8, 23.8, 65.6 }	187	15	84	4.2(m)
P_2	Removing trees from 10-meter buffer area	{100, 200, 500}	0	100	100	1.6 $(ea.)$
P_3	Cutting dead and down limbs, pruning,	{0.1, 0.2, 0.25}	0	96	100	485.5 (m^2)
P_4	Removing Grass, herbaceous, and shrubs	{10.8, 21.5, 32.3}	226	98	99	40.5 (m^2)
P_5	Removing Grass, herbaceous, and shrubs	{10.8, 21.5, 32.3}	226	100	100	442(m^2)
P_6	Removing combustibles	{113, 310, 500}	0	92	100	1$(ea.)$
P_7	Removing flammables	{0, 0, 0}	0	26	100	1$(ea.)$
P_8	Removing hazardous material	{0, 0, 0}	0	91	17	0.2$(ea.)$
P_9	Re-roofing	{3.3, 5.4, 16.2}	415	63	93	281.5(m^2)
P_{10}	Replacing/Enclosing open foundation	{10.8, 21.5, 32.3}	202	17	21	87.5 (m)
P_{11}	Replace siding with fire resistant material	{1, 2, 4}	202	24	96	190.5(m^2)
P_{12}	Capping vents and aluminum soffit (m^{-1})	{65.6, 82.02, 101.7}	0	21	99	19.7$(ea.)$
P_{13}	Replacing wood deck (m^2)	{53.8, 86.1, 107.6}	116	98	96	8.4(m^2)

Attribute Identifier (1)	Description (2)	Unit Cost [USD] {min, mean, max} (3)	Fixed Cost [USD] (4)	High Vulnerability Homes (%) (5)	Very high Vulnerability Homes (%) (6)	Average Quantity to Retrofit (unit) (7)
P_{14}	Enclosing fuel traps (m^2)	{107.6, 161.5, 215.3}	0	97	100	6.7(m^2)

As shown in Table III-2, changing the ground cover (P5) appeared on the feasible retrofit plans of all properties whereas covering foundation/replacing foundation cover (P10) appeared on the feasible retrofit plan of a relatively small percentage of the properties. As is shown in Table III-2, the average area of a building in the study area is 281 m2, which is relatively large. The reason for this magnitude is that the properties in the study area belong to wealthy suburbs where large properties are expected.

The target for vulnerability rating reduction is to decrease the vulnerability level of parcels with high and very high vulnerability ratings to at least a moderate level. Therefore, the acceptable rating, R^t, is set at 60 points. The model discussed in Figure III-2 is coded in MATLAB version 2015. Using a Monte Carlo sampling, $ITR = 2400$ cost scenarios were simulated, the unit cost of each retrofit, c_{pi}, is drawn from a three-point PERT distribution. The total number of iterations required to simulate a normally distributed probabilistic outcome is calculated based on the target confidence interval, estimated standard deviation of the output, and margin of error. The minimum cost of retrofit, C_i^*, for an average house in the study area had a standard deviation of 102 which calls for a minimum of 1600 iterations to achieve a confidence interval of 95%. The minimum total cost dataset that resulted from the optimization with various cost scenarios has 933,600 (2400×389) observations. 95% of the optimal costs are below $10,000, and 81% below $4,000. An indicator of the cost effectiveness of the retrofit measures could be the frequency at which retrofit measures are part of the optimal retrofit plan. In Figure III-3, these frequencies are expressed in terms of the percentage of the total number of runs (2400).

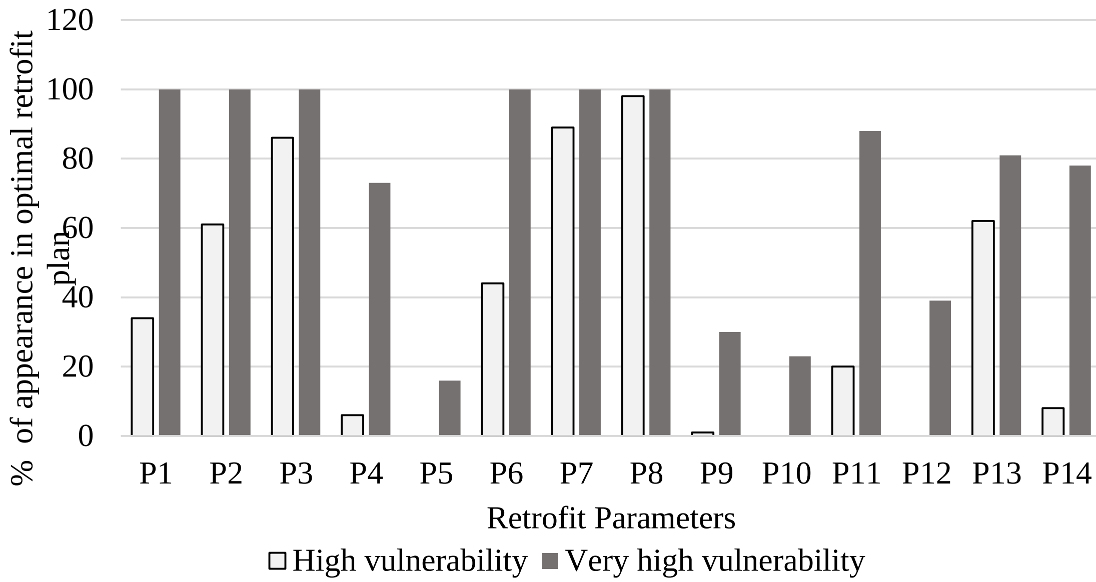

Figure III-3: Percentage of appearance of each retrofit measure in optimal retrofit plan of high and very high vulnerability homes

The results in Figure III-3 suggest that, as expected, the costless retrofit measures “removing flammables” and “removing hazardous materials” away from the building are the most frequent measures in the optimal plan set for both high and very high vulnerability homes. In general, structural retrofit measures are less selected in the optimal retrofit plans compared to the site retrofit measures for both high and very high vulnerability properties, which is in agreement with findings from Stockmann et al. (2010). Implementing retrofit measures on the ground cover is the least frequent in the optimal plans among the site-related measures for both groups of properties, which may be due to their relatively high fixed cost. As for the structural retrofit measures, replacing exterior walls and attachments seem to be the most optimal measures, whereas re-roofing, covering, replacing foundations, and screening vents and eaves seem to be the least effective measures based on their appearance on the optimal retrofit plan.

6. Cost model for wildfire vulnerability mitigation in residential properties

To account for the variation in the cost of optimal retrofit plan based on the size of the properties, as well as the vulnerability rating the following regression analysis is conducted using the results generated by the optimization:

$$\overline{C^*} = \beta_0 + \beta_1 R^0 + \beta_2 {R^0}^2 + \beta_3 {R^0}^3 + \beta_4 {R^0}^4 + \beta_5 \mathrm{A} + \beta_6 \mathrm{A}.R^0 \quad \text{Eq. III-5}$$

The average minimum total cost of retrofitting for each home as the dependent variable,$\overline{C^*}$, is explained by initial vulnerability rating R^0 and its higher orders (${R^0}^2, {R^0}^3$, and${R^0}^4$), floor area of the building, A, and the interaction term between area and vulnerability rating (A.R^0). The functional form shown in equation five is selected based on the non-linearity assumption made by Busby and Albers (2010); they argue that a cost function for vulnerability mitigation should be concave in vulnerability. In other words, the total investment required for decreasing vulnerability to wildfire should increase by the initial vulnerability rating but at a decreasing rate. Hence, negative coefficients for even powers of R^0 are expected for this cost model. Different powers of R^0 are added to cost model until a significant improvement in the adjusted R-squared was observed and the coefficients of the added terms are statically significant. In addition, the coefficient of the interaction terms is statistically significant suggesting that the interaction effect should be considered between the area and initial vulnerability rating. In other words, the effect of high initial rating in the total cost is different for different building sizes. The marginal cost of initial vulnerability rating in this model would be estimated from the following equation:

$$\frac{\partial \overline{C^*}}{\partial \mathrm{R}} = \beta_1 + 2\beta_2 R + 3\beta_3 R^2 + 4\beta_4 R^3 + \beta_6 \mathrm{A} \quad \text{Eq. III-6}$$

The regression dataset includes the associated observations for 389 properties, all of which were subject to the retrofit plan optimization. Descriptive statistics of the regression variables are shown in Table III-3.

Table III-3: Descriptive statistics of the regression dataset

Variable	Mean (Standard Deviation)	Min	Max
$\overline{C^*}$ (USD)	2028.6 (3230.8)	0	23,045
R^0	83.4 (14.2)	60	117
A (m^2)	281.5 (155.4)	43.5	1008.7
# observations: 389			

Note: Numbers in parentheses are standard deviations

The results of the cost model regression for wildfire vulnerability mitigation in residential properties is presented in Table III-4.

Table III-4: Regression Results

Variable	Coefficient	Standard Error	P>|t|
R^0	8865.026	5195.700	0.089
${R^0}^2$	-163.134	91.122	0.074
${R^0}^3$	1.280	.701	0.069
${R^0}^4$	-.004	.002	0.072
A	-31.219	3.387	0.000
$A.R^0$	0.434	.040	0.000
$constant$	-173061.4	109625.2	0.115
$\bar{R}^2 = 0.71$			
# observations: 389			

The adjusted R-squared for the regression is 0.71 meaning that 71 percent of variation in the total retrofit cost is explained by the model. Estimated costs based on the regression results are shown in Figure III-4 as a function of the initial vulnerability rating and the building area.

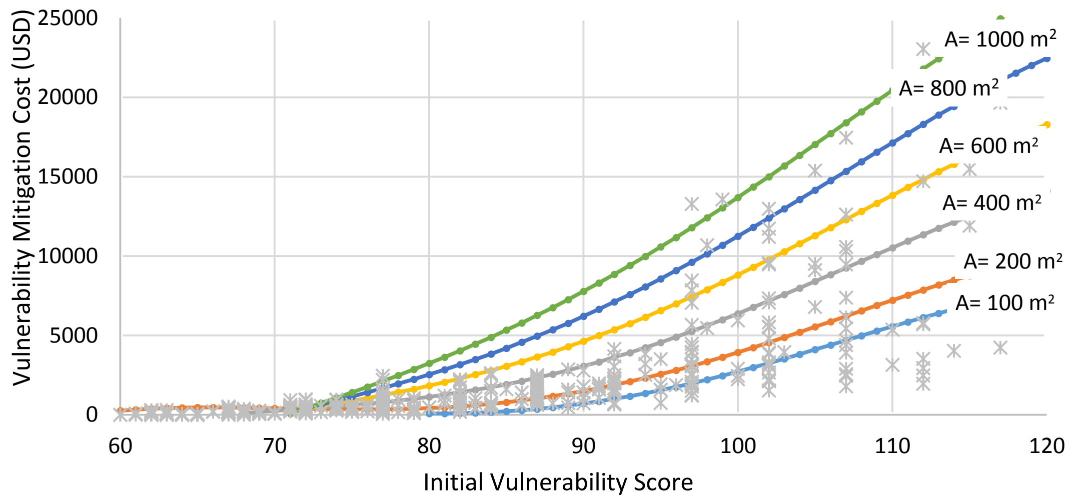

Figure III-4: Wildfire retrofit cost model

Fig. 4. Vulnerability mitigation costs based on property's initial vulnerability score and floor area

As the regression results suggest, for an average home with 281.5 m^2 building area and an initial vulnerability rating of 83, the marginal retrofit cost is about 119 USD. In other words, an additional vulnerability rating unit at the building area of 281.5 m^2 means additional 119 USD to the minimum retrofit costs.

7. Summary and Conclusions

The range of findings for this study is compared with the findings from Stockmann, et al. (2010). They found a maximum cost of $19,258 per house to mitigate wildfire vulnerability, for 291 houses in Montana where median value of the homes (in Missoula, Montana) was $237,300 in 2010. The range of costs found for this study area, with a median home value of $272,700, is between zero and $23,045, with 95% of the cost estimates being below \$10,000. For an average home in the study area, with 281.5 m^2, the cost of reducing vulnerability to moderate level is 2,029 dollars. Using a polynomial functional form in regression analysis (i.e. incorporating higher degrees of the initial vulnerability ratings in the model), a cost model is resulted using the optimal cost data. Polynomial regression of degree four with negative coefficients for the even powers of the initial vulnerability score appropriately reflects the concavity of the cost function in initial vulnerability level. In addition, the interaction effect between the building area and initial vulnerability in the cost model is addressed by an interaction term ($A.R^0$). The regression results suggest that for an average property in the study area, with 281.5 m^2 and initial vulnerability rating of 83.4, an extra unit of vulnerability, will add 119 dollars to the minimum cost of retrofit.

In addition to provision of a retrofit cost model for the community under study, the result of the proposed model is an optimal plan for each home. Not only can such an optimal retrofit plan benefit homeowners and wildfire managers in dealing with wildfire risk, but also insurance companies can benefit from this model to adjust their mitigation contingency requirements and premiums. Homeowner assistance grant programs such as Hazard Mitigation Assistance Grant by Federal Emergency Management Agency and local Cost Share Programs can also take advantage of the proposed framework in order to estimate and prioritize homeowner vulnerability mitigation grants.

The cost data can vary between communities, and as a result, the parameters of the cost function, and the optimal cost range changes would also vary. However, the suggested framework is flexible and could be implemented in different communities, and also for other types of natural hazards. Homeowner preferences in post-retrofit mode (material and or design) of the land and building element is considered in this study. Improving information on the homeowner preferences could reduce the uncertainties involved in estimation of unit costs of retrofit measures and help improving the model’s accuracy. In communities that are required to have a CWPP, reassessments take place for updating the CWPP. The difference between the evaluation cards associated with consecutive assessments carry information on homeowners’ preferences in selecting from the retrofit measures. Moreover, surveying homeowners is a direct approach to understanding homeowner preferences.

Moreover, it is assumed that there is no correlation between the impacts of implementing two retrofit measures which leads to an overestimation of the costs of retrofitting and favors a more cautionary retrofit decision. However, in order to reach the lowest cost of implementing retrofit measures, the correlation between different retrofit measures should be considered. Another limitation is the lack of accuracy on the estimation of amount of work for some of the retrofit measures, which could be improved by using LiDAR remote sensing methods.

Acknowledgements

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IV. Dynamics of Homeowner Mitigation Response to Wildfire Hazard

Abstract Wildland Urban Interfaces are exposed to wildfire hazard. Natural and manmade processes have resulted in an increased frequency and severity of wildfires. Expansion in the size of WUIs calls for a sustainable wildfire management plan. Homeowner involvement in mitigation is considered by many researchers the key element of a wildfire resilient community. Given that residential property is the major asset for the majority of homeowners, they are likely to protect the value of their homes through investment in mitigation activities. Experimental studies, surveys, and interviews with homeowners in wildfire prone WUIs have shown that homeowners de facto see mitigation as a process that takes multiple years to be completed. The investment decision made by homeowners through a five-year period is investigated in this study. Investment options are private land treatment and adding a wildfire protection coverage to their insurance policy by purchasing extra premium. The objective is to maximize the expected value of the investment throughout the decision period. Three factors that can affect the outcomes are investigated, namely, homeowner's preference on dynamic trend of investment, time value of money, and the effect of mitigation contingent insurance. The methodology used is a Mixed Integer Programming, where the choice of coverage options is assumed of integer variables and the investment on retrofit measures are assumed of continuous format. The results of our study show that a homeowner who prefers to invest more on their treatment activities earlier than later achieves a higher expected value of investment compared to a homeowner who would like to pays more towards the end of the decision period.

1. Introduction

Wildland Urban Interfaces (WUIs) are where the vegetation of the undeveloped forest and residential buildings interdigitate (Radeloff et al. 2005). Due to WUIs' adjacency to forests, these zones are highly susceptible to wildfire hazards. Wildfires, are either man-made or lightning ignited on the forests (Syphard & Keely 2015). They become problematic when due to adverse weather conditions such as wind, speed and temperature the flames are reinforced to feed on the vegetation of the forest and propagate. When there is a community close to forest, flames threaten assets and even lives of the community members. Between 2002 and 2011, a total of $7.9 billion was reported for insured losses to wildfire which showed a $6.2 billion increase over the preceding decade (Haldane 2013; Calkin et al. 2014).

Due to an increase in global temperature, drought, and fuel build-up resulting previous suppression-focused forest policies, the risk of high intensity wildfires is increasing (Fischer, Spies, & Steelman 2016; Cook et al. 2016). On the other hand, there is an increasing interest in living close to the forests and in the WUIs (Hjerpe, Kim, & Dunn 2016). Recent estimates place the size of the WUIs in the US at 190 million acres (770,061 km2), 44 million homes and 99 million people (Martinuzzi et al. 2015), with nearly 40 million people at significant wildfire risk (Haas et al. 2013). The worsening of wildfire regimes and increase in the size of WUIs, together, mean higher residential vulnerability, which calls for sustainable wildfire management and response. Homeowners are believed to play an important role in achieving this sustainable plan. Their most important responsibility is to protect their properties to wildfire (Mockrin et al. 2015; Calkin, Charnley et al. 2015; Cohen, & Finney 2014).

To confront natural hazards, homeowners make investment decisions for two types of insurance: market insurance and self-insurance (Carson, McCullough, & Pooser 2013). Whereas insurance companies underwrite the losses accrued to their clients in the aftermath of a disaster, self-insurance includes undertaking preventive improvements through the implementation of risk averting activities within the private property to reduce the probability or severity of potential in the case of a natural disaster. Therefore, homeowners need to invest on a combination of market insurance and self-insurance. The focus of this study is on homeowners' decisions for confronting wildfire hazard in Wildland Urban Interfaces (WUIs).

Self-insurance in WUI areas requires changing or rearranging the physical setting of the property such as changing the roofing system, siding material, ground cover, among all (Cohen 2000, Stockmann et al. 2010). Studies on homeowner preferences have shown that homeowners' investment on self-insurance corresponds to a multi-year decision as opposed to a one-time decision (Brenkert-Smith et al. 2006; McCaffrey et al. 2011). This is attributed to the resistance of the homeowners to perform physical changes to their properties as well as budget constraints. As for market insurance, in locations with high risk of wildfire, if available, the eligibility for insurance coverage is contingent on undertaking a minimum amount of self-insurance through the implementation of risk averting activities by homeowner. In some cases, where there is an extreme wildfire risk, insurance companies may cancel related policies altogether (Keiter 2006).

An investment schedule including both market insurance and self-insurance is subject to an optimization problem with the objective of maximizing the expected value of homeowner's investments. The effectiveness of self-insurance improvements can be reflected in a damage probability function. The objective of this investigation is to formulate the investment decision of homeowners over a multi-year investment plan considering the effects of budget and market insurance policy constraints. Using a mixed-integer programming, the optimal annual investment for market and self-insurance are derived from the optimization. A case study is used to discuss the effects of various parameters on the investment schedule. The case study is solved both with and without considering the time value of money and considering contingency and budget constraints.

The results show that in the absence of budget constraints, and mandates on mitigation, the homeowner's optimal choice would be to fully invest on insurance purchasing the broadest wildfire hazard insurance coverage. When there is a mandate on performing mitigating retrofit measures, considering the budget constraint the homeowner would have a descending mitigation investment preference (invests more at the beginning of the multi-year period and decreases the investment throughout time). In this case, results show that the homeowner would achieve a higher expected value of investment than a homeowner with ascending investment preferences.

2. Background

Studies on homeowner investment for wildfire risk mitigation can be divided into two categories, namely, stated preference models and analytical models. Stated preference models try to find homeowners' preferences with regard to investments and its timing, whereas analytical models seek optimal or near optimal solutions to the homeowners' expected utility maximization, without necessarily accounting for the socio-cultural attributes of homeowners. Methods and findings within these two research lines are summarized in the following sections.

2.1. Homeowner Preferences

Prior studies have explored drivers and obstacles of homeowners insurance using surveys and experiments. Participants in different studies have stated that their budget dictates the timeline of their investment (Brenkert Smith et al. 2012; McCaffrey et al. 2011; McFarlane et al. 2012; Champ, Donovan, & Berth 2013). When budget is available for both types of insurance, the tradeoff homeowners make between the two insurances, self-insurance and market insurance, is not clear. Some studies argue that homeowners may see market insurance and self-insurance as substitutes rather than complements (Hjerpe, Kim, Dunn 2016, Talberth et al. 2006), and argue that without sufficient enforcement, the homeowners will be reluctant to invest on self-insurance. One mechanism of enforcing self-insurance is to make market insurance's coverage available only to homeowners who have undertaken a minimum amount of self-insurance through implementation of risk averting activities.

However, even when it is known that homeowners are willing to invest on both types of insurance, it is not clear how homeowners mix their insurance investments. Talberth et al (2006) and McKee et al. (2004), using a survey and an experiment, respectively, measured homeowners' total investment on four wildfire risk response measures, namely, market insurance, self-insurance, community land treatment, and public land treatment. Using a log odds measure, these studies estimated the proportion between each one of the four measures and the total investment amount. Their findings showed that homeowners tend to allocate the greatest portion of their investments on market insurance (about 65%) compared to the other three investment options; self-insurance comprised of 2 to 16 percent of total investment depending on the availability of cost-share or disaster recovery programs. Other factors that are shown to be positively correlated to homeowner's decision on investment are self-efficacy, attachment to the place, trust in social systems, peer pressure, efficiency of information, perception on wildfire hazard and climate change, among others factors (Anton & Lawrence 2016, Brenkert-Smith, Meldrum, & Champ 2015; Crow et al. 2015; Brenkert-Smith, Champ, & Flores 2006; Martin, Martin, & Kent, 2009; McFarlane, Mc Gee & Faulkner 2012; McCaffrey 2004).

2.2. Utility Maximization

Homeowner's response to wildfire risk includes avoiding, transferring, reducing and accepting the results of a wildfire (Talberth et al. 2006). Avoiding wildfire risk can be manifested by moving out of the WUI (Carson, McCullough, & Pooser 2013). However, available statistics on WUI homeowners show that rarely WUI homeowners move out of the WUIs even after nearby catastrophic wildfires (Price Water House 2001), and there is no evidence of buy-outs due to the risk of wildfires. Investment in market insurance and self-insurance are forms of risk transferring and reduction, respectively.

Shan et al. (2016) proposed a utility function for investment on market and self-insurance in the case of hurricane risk in North Carolina. They formulated the utility function for 12 groups of buildings categorized by their architectural characteristics (e.g., roofing system or number of garages, among others), their location with respect to the coastline and their occupancy, in 143 census tracts in a low lying coastal region in North Carolina. A set of 143 hurricane retrofit options, combined with no-action, and insurance provided 288 decisions for homeowners. With the assumption that a rational homeowner has perfect information on risk, insurance, and retrofit options, it was concluded that the homeowner would adopt a decision that yields maximum utility. Building groups were subject to 97 hurricane scenarios and the maximum utility of all combinations of decision and hurricane scenario was derived by enumeration. Their results showed that self-insurance and market insurance could be substitutes, but this is not always the case. They showed that the availability of funds for self-insurance played a very important role, where there is a hypothetical subsidy for homeowner retrofit measures provided by the government, about 450,000 homeowners would switch to implementing retrofit measures as self-insurance on their property.

The utility of WUI homeowner when confronting wildfire was proposed by Busby and Albers (2010) in a game theoretic context. Their model considered the case of multiple decision makers and their interactive decision-making process. Homeowners' expected utility was defined as the homeowners' liability for their loss multiplied by their property value (both building and amenity values), times the resilience of the values in a given wildfire situation. The resilience term in the utility function was defined as the probability that the properties stand after a wildfire, which is a function of mitigation efforts within (self-insurance activities) and around the property. An important characteristic of the resilience function is that it is increasing with a decreasing rate, in that, initial mitigation efforts reduce the probability of damage to a greater extent compared to following mitigation efforts.

Busby, et al (2013) expanded on the previous model to account for insurance, dynamics of the game, and misinformation of the players, that are two adjacent private landowners. Individual utility in this model was based on the assumption that wildfire probability changes over time, but it is predetermined. Upon arrival, fire burns both properties but to different extents based on the available fuel on the property. The damage function was assumed to be deterministic. Fuel stock on each property also changed over time given the implemented treatment actions as well as the fuel growth-back rate. Hence, building components that could act as fuel were implicitly excluded from the definition of fuels. The utility function of an individual homeowner was composed of the property value minus the insurance and treatment cost plus the expected value of the property given future actions and wildfire probabilities.

While the literature has looked at homeowners' socio-economic incentives and dis-incentives for investing on self-insurance and market insurance or the interaction between neighbors confronting wildfire, the dynamics of homeowners' investment decision is not accounted for. In this study, the utility of an individual homeowner is modeled accounting for the stochastic nature of the outcomes of the homeowner's investments on wildfire risk mitigation. The optimal investment decision of homeowners is modeled over the course of multiple years and accounting for the cumulative effect of prior self-insurance investments on reducing the probability of damage in following years. The multi-year investment plan allows investigating how investment trend (change of investment amount over time) through years can shape the expected value of the homeowner's mitigation investments. The probability of wildfire occurrence each year is assumed to be exogenous to homeowner's decisions and therefore homeowners do not impact the probability of wildfire in the proposed model. However, in a scenario where a wildfire arrives at the community, homeowner's decision could impact his loss due to wildfire through a probabilistic loss function. The budget constraint is also taken into account in this model. A mixed-integer optimization model is proposed to find the optimal value of the investments on self-insurance and market insurance. This method enables investigating the impact of different policies such as market insurance contingency on self-insurance. The homeowner is assumed to be rational with complete information about the costs of self-insurance and market insurance, and the loss probability.

3. Problem Statement and Methodology

The objective of this optimization model is to maximize the homeowner's expected value of investment over a multi-year interval. Objective function, decision variables, and constraints of the model are discussed in following sections.

3.1. Decision Variables

Decision variables, in this study, are amounts of self-insurance and market insurance investment at each time period.

3.2. Objective function

The objective function is shown in the following equation:

$$\max_{t} \sum_{I_a^t, I_i^t} \frac{EV^t}{(1+r)^t} \qquad \text{Eq. IV-1}$$

The term r in the denominator is the discount term or time value of money. The expected value of the investment at each time is as follows:

$$EV^t = -I_a^t - I_i^t - p^t L + p^t \sum_{k=1}^{K} x_k^t . {C_k}^t . e_k^t \qquad \text{Eq. IV-2}$$

Where EV^t is the expected value of investments at the end of year t, ${I_a}^t$ is the amount of investment on self-insuring, risk averting activities in year t, ${I_i}^t$is the annual cost of market insurance which may change by homeowners' decision on the insurance coverage (k)per year t; p^t is the probability of damage during wildfire season of year t.

$x_k^t \in \{0.1\}$ is the binary variable which takes the value of 1 for coverage k if homeowner is choosing that coverage, and zero otherwise. The amount of loss due to wildfire and compensation made by insurance company in year t are represented by L and C^t, respectively. Term e_c^t is a binary variable that controls for homeowner's eligibility for a chosen coverage k.

3.3. Constraints

One of the constraints is that homeowners only choose one of the coverages amongst all available coverages:

$$\sum_k x_k^t = 1 \quad \text{Eq. IV-3}$$

In hazard prone areas such as WUIs, insurance companies usually offer mitigation contingent coverage plans (Haines, Renner, and Reams 2010). In such cases, the availability of market insurance coverage for wildfire is contingent on homeowner undertaking minimum self-insuring efforts on his property. The test for market insurance eligibility is shown in Eq. 4:

$$e_k^t = \begin{cases} 1 & if \ \sum_{t \in T} \frac{{I_a}^t}{(1+r)} \geq E_k^{Min} \\ 0 & Otherwise \end{cases} \qquad \text{Eq. IV-4}$$

Where, E_k^{Min} is the minimum investment required for coverage k to be available to the homeowner. In this study, it is assumed that maximum amount of investment on self-insurance is constrained to a given percentage of the home value:

$$\forall t \in T: {I_a}^t \leq \alpha . V \quad \text{Eq. IV-5}$$

The constraint on self-insurance investment reflects the resistance of the homeowners to a significant physical change on their properties. Where V is the home value, and $\alpha \in [0,1]$ is a maximum annual treatment investment multiplier. In addition to the annual constraint on the self-insurance investment amount, the total annual investment on insurance (both self-insurance ${I_a}^t$and market insurance ${I_i}^t$) is restricted to an annual investment cap (I_0), which is assumed to be the disposable income of the homeowner (Talberth et al. 2006) as shown in Eq. 6:

$${I_a}^t + {I_i}^t \leq I_0 \quad \text{Eq. IV-6}$$

Supposing that the homeowner is committed to implement a minimum amount of self-insuring activities over the decision interval, there would be a minimum amount of cumulative investment on self-insurance as defined in Eq. 7:

$$\sum_{t \in T} \frac{{I_a}^t}{(1+r)} \geq I_{Min} \quad \text{Eq. IV-7}$$

Where I_{Min} is the cost of the adopted retrofit plan. The probability of damage to the property due to a wildfire that has reached a community depends on the implementation of risk averting activities implemented by the homeowner. Busby and Arbor (2010) suggest that the probability of loss is reduced as the amount of risk averting activities increase, however, the rate at which the probability is decreased is diminishing. In other words the rate of decline in probability of loss is higher in initial amount of risk averting efforts but this rate declines as more effort is spent:

$$p^t = \frac{\mathrm{A}}{\mathrm{B} + \ln(\sum_{y=1}^{y=t} {I_a}^y)} \quad \text{Eq. IV-8}$$

Where, A and B are adjustable parameters that could be defined using available models. The typical assumption about physical damage from wildfire is that when wildfire reaches a building, the damage is high enough to assume total loss or destruction (Cohen 2000; Shafran 2008). In this study, it is assumed that the outcome of a wildfire damage is 90% loss of the value of the property:

$$L = 0.9V \quad \text{Eq. IV-9}$$

The insurance compensation to the homeowner is based on the insurance coverage purchased in the year of the wildfire. Whereas the amount of investment on physical land treatment is assumed to be continuous, the choices of insurance plans are assumed to be discrete. In other words, there are countable finite coverage options for homes in the WUI. The homeowner makes the decision regarding the self-insurance amount (I_a^t) as well as the coverage option (C^t):

$$C^t = \beta_k V \qquad \text{Eq. IV-10}$$

Where $\beta_k,\ k \in \{1,2,\dots,K\}$ is the maximum wildfire loss covered by purchasing market insurance option k among offered plans. The investment on market insurance is the price of premium for option k (M_k):

$$I_i^{\,t} = M_k \quad \text{Eq. IV-11}$$

The optimal decision set for the expected utility maximization problem is shown by the set $\{(I_a^{t^*}, C^{t^*}): t \in \{1,2,\dots,t\}\}$.

The optimization problem is solved using mixed integer programming where the risk averting treatment decision variables are of continuous type and the insurance coverage choices are integer variables. The objective function is non-linear and constrained by both linear and non-linear functions. The size of the solution space is a function of the number of years in the planning horizon and the available coverage options. A feasible decision satisfies Equations 3 through 11.

Both Generalized Reduced Gradient (GRG) and Evolutionary algorithms are implemented to solve the optimization problem using Microsoft Excel. Whereas GRG is a nonlinear optimization tool, evolutionary algorithms are intelligent search algorithms to explore complex or large solution space efficiently, rather than completely (Kalhor et al. 2011). The preference of the homeowner in spending their money on self-insurance during a multi-year investment decision is reflected in a specific “trend” constraint considered in the model. To investigate how homeowners’ attitude towards their investments on mitigation impacts the expected value of their investments, two trends are considered on the investment decision variable:

- *Trend 1*: A homeowner who adopts Trend1, tends to invest more as time passes (Eq.12-a).
- *Trend 2*: A homeowner who chooses Trend2 spends more in the beginning and then reduces their investment amount over time (Eq.12-b).:

$$
\begin{aligned}
&{I_i}^t \geq {I_i}^{t+1} \ (a) \\
&\qquad\qquad\qquad\qquad \text{Eq. IV-12} \\
&{I_i}^t \leq {I_i}^{t+1} \ (b)
\end{aligned}
$$

4. Model Implementation and Results

Data for the numeric example were retrieved from the study by Stockmann et al. (2010). Their study area was the Bitterroot Valley in Montana that included Missoula and Ravalli counties. In their studies, they modeled 291 houses using the Structural Ignition Assessment Model (SIAM) developed by Cohen (1995). SIAM estimates the probability of structural ignition given the building materials and defensible space's setting. Stockmann, et al. (2010) estimated the retrofit costs to reduce the ignition probability of the houses, before and after implementing seven retrofit schedules. They estimated the average costs of different retrofit schedules as well. The probability function given in equation (7) was derived by plugging the values from the Stockman's results to estimate parameters A and B. As result, the probability function was estimated as follows:

$$P = \frac{5.58}{5.64 + \ln(\sum_{y=1}^{t} I_a^t)} \quad \text{Eq. IV-13}$$

The average median home value in Bitterroot Valley is \$236,000 according to the 2014 U.S. Census. To demonstrate the proposed methodology, the length of the planning horizon was set to five years ($T = 5$). Data on wildfire specific insurance purchases and coverage is very limited due to the private nature of insurance policies in most WUIs. As a result, the coverage costs and options for the case study were hypothetical (similar to the model by Busby, Amacher, and Haight 2010). The values of the model parameters are summarized in Table IV-1, and the values of insurance related parameters are shown in Table IV-2

Table IV-1: Values assigned to optimization problem

Variable	Definition	Value
V	Home value	\$250,000
T	Planning horizon	5 years
α	Hypothetical property change acceptance level of a homeowner	%
I_{Min}	Minimum total cumulative investment on self-insuring retrofit measures at the end of the decision-making period	\$19,000
I_0	Maximum annual investment amount	\$12,000
K	Number of insurance coverage options	4
r	Discount rate	0.01

Table IV-2. Market insurance related parameters

Variable	Definition	$k = 1$	$k = 2$	$k = 3$	$k = 4$
C	Coverage	0%	50%	70%	90%

M_k	Premium price	\$0	\$1000	\$2,000	\$4000
E_c^{Min}	Contingency Value	0	0.1 I_{Min}	0.2 I_{Min}	0.4 I_{Min}

The price of premium for 70% coverage was assumed to be twice the price for 50% coverage, and the price of 90% coverage was set to be three times the price of 50% coverage. Suppose that effectiveness of an investment plan, I_t, is defined as the ratio between the reduction of loss before (superscript b) and after (superscript a) implementing I_t, and the amount of investment, I_t:

$$EF = \frac{EV(loss^b) - EV(loss^a)}{I_t} \quad \text{Eq. IV-14}$$

Therefore, the effectiveness of investing in self-insurance treatment activities (I_{min}) could be estimated as:

$$EF = \frac{P(I_{min}).L - P(0).L}{I_{min}} \qquad \text{Eq. IV-15}$$

And, for the investment on market insurance the effectiveness is

$$EF = \frac{P(0).C^k.V}{M^k} \qquad \text{Eq. IV-16}$$

For the case study, the effectiveness of the self-insurance treatment was estimated at 0.74; the effectiveness of the market insurance investment ranges from 124 for 50% coverage to 56 for 90% coverage options. It is worth reminding that this insurance price represents the additional charge for insuring property against wildfire. The spreadsheet used by Excel Solver is shown in Figure IV-1.

year	Treatment Investment	Accuumulated Treatment	Investment With Time	Cumulative Investment Time	Pd	0% Coverage	50% Coverage	70% Coverage	90% Coverage	Sum Bin	Contingency Value	Coverage%	Investment Insurance	Total Investment	EV	EV_Time
1	8,000	8,000	8,000	8,000	0.381	0	1	0	0	1	2,470	1	1,000	9,000	-45,012	-45,012
2	8,000	16,000	7,921	15,921	0.364	0	0	1	0	1	4,940	1	2,000	10,000	-27,191	-26,922
3	3,150	19,150	3,088	19,009	0.100	0	0	0	1	1	9,880	1	3,000	6,150	-6,150	-6,029
4	0	19,150	0	19,009	0.006	0	0	0	1	1	9,880	1	3,000	3,000	-3,000	-2,912
5	0	19,150	0	19,009	0.006	0	0	0	1	1	9,880	1	3,000	3,000	-3,000	-2,883
∑	19,150			19,009												-83,757

Variable	Min	Max	Actual
Annual Treatment Investment	0	8,000	NA
Total Investment	0	12,000	NA
Accumulated Treatment investme	0	19,000	
Trend	Decreasing by time		NA
Minimum 50% Coverage			0.130
Minimum 70% Coverage			0.260
Minimum 90% Coverage			0.520
Contingency of coverage coeff (β.			0.5

Variable	Min	Max	Actual
HomeValue			236,000
Discount Rate			0.010
Price 50% Coverage			1,000
Price 70% Coverage			2,000
Price 90% Coverage			3,000

Figure IV-1: Spreadsheet model configuration

The expected value of no investment is -\$210,140 every year, and adds up to about one million dollars over a period of five years.

4.1. *Case I: No contingency constraint* ($e_c^t = 0$)

When all constraints, equations 3-10, were relaxed, results show that the optimal solution for the homeowner is to invest only on market insurance and to purchase the maximum coverage available ($I_a^{t^*} = 0, and\ C^{t^*} = 90\%,\ \forall t \in T$). The expected value of investment, in this case, depends on the 90% coverage's premium. The expected value ranges from -\$14,706 for a 90% coverage at a premium of \$3,000/year, to -\$58,824 for a 90% coverage at a premium of \$12,000/year. Based on the price of market insurance, the expected value of the homeowner in this case can range from -\$14,706 to -\$58,824 for 90% coverage's premium price of \$3,000 to \$12,000, respectively.

4.2. *Case II: Unavailability of market insurance ($\boldsymbol{k} \in \{\mathbf{1}\}, \boldsymbol{C^1} = \mathbf{0}\%$)*

When there is no market insurance covering losses to wildfire, results show that the optimal solution would be to invest all the available budget on self-insurance until the minimum accumulated self-insurance investment is reached ($I_a^{t^*} = I_0 \; for \; t|_{\sum_{y=1}^{y=t} \frac{I_0}{(1+r)^t} \leq I_{min}}$). Compared to the previous case, the cumulative expected value of investment over the course of five years is equivalent to one third.

4.3. *Case III: Self-Insurance investment trend (equations 11-1 and 11-2 are binding)*

In order to control for the homeowner's preference on investment trends, two identical homeowners with different preferences on investment trend are compared. Homeowner A chooses a "decelerating" self-insurance investment trend, whereas, homeowner B prefers an "accelerating" self-assurance investment. In other words, the preference of homeowner A is manipulated by constraint shown in equation (11-1) and trend preference of homeowner B is shown in equation (11-2). The estimated optimal values of investment on self-insurance and market insurance coverage (${I_a}^{t^*}$, and C^{t^*}) are shown in Table IV-3 for homeowners A and B.

Table IV-3: Results of the optimization for homeowners A and B

t	Homeowner A	Homeowner B

	$\boldsymbol{I_a}^{\boldsymbol{t}^*}$	$\boldsymbol{C}^{\boldsymbol{t}^*}$	$I_i{}^t$	$\sum_{t\in T} \frac{I_a{}^t}{(1+r)}$	p^t	$\sum_t EV$	$\boldsymbol{I_a}^{\boldsymbol{t}^*}$	$\boldsymbol{C}^{\boldsymbol{t}^*}$	$I_i{}^t$	$\sum_{t\in T} \frac{I_a{}^t}{(1+r)}$	p^t	$\sum_t EV$
1	8,000	70%	2,000	8,000	0.381	-11,000	3,800	50%	1,000	4,000	0.402	-42,742
2	8,000	90%	3,000	15,843	0.364	-21,891	3,800	70%	2,000	7,922	0.383	-66,375
3	3,300	90%	3,000	19,015	0.360	-28,067	4,000	90%	3,000	11,766	0.372	-73,237
4	0	90%	3,000	19,015	0.360	-30,979	4,000	90%	3,000	15,536	0.365	-80,031
5	0	90%	3,000	19,015	0.360	-33,862	4,000	90%	3,000	19,231	0.359	-86,854

The optimal decision for homeowner A is to invest up to the investment value which reflects his resistance to change ($\alpha.V$) in the first years to complete their minimum investment amount, and allows funds for purchasing maximum coverage from the insurance company as soon as their funds and contingency constraints allow. The expected value of this investment is -$33,862. In contrast, homeowner B's optimal decision is to invest on self-insurance uniformly through the decision interval. These results imply that in order to reach optimal amounts in the case of imposed diminishing investment constraint (Eq. 12a), the best solution lies on the boundary value ($I_i{}^t = I_i{}^{t+1}$) yields the optimal value, dominating the absolute inequality condition $I_i{}^t > I_i{}^{t+1}$.

4.4. Case IV: The effects of different amounts of resistance to change (α)

In order to test the effect of homeowner's resistance to physically change or alter their properties through self-insurance?, the expected utility is calculated for different values of α (equation 4). The amount αV is an indicator of the total physical change to their property a homeowner is willing to accept, which is expressed in dollar terms. $0 \le \alpha \le 1$

is the factor of home value that expresses this tolerance of change as a percentage of home value.

Results show that the value of α affects homeowner's maximum investment on self-insurance. Figure IV-2 shows the optimal cumulative expected value for two amounts of α, 0.034, and 0.042, which result in the total annual threshold of $8,000 and $10,000, respectively. As is shown in the figure, for most insurance contingency values ($\mathrm{e}_{\mathrm{c}}^{\mathrm{t}}$), the optimal cumulative expected value ($\sum_{t=1}^{T} EV_t^*$) are the same, however, when the contingency values reach to 0.21 and higher, the optimal expected value for a homeowner with a change threshold of $8,000 falls below the optimal expected value of the homeowner with a change threshold of $10,000. This decrease could be attributed to the fact that since the resistance to change inhibits homeowner from satisfying mitigation contingency constraint earlier in the investment decision interval. Consequently, the expected value of their utility decreases as the minimum required mitigation for eligibility to purchase insurance e_c^t increases.

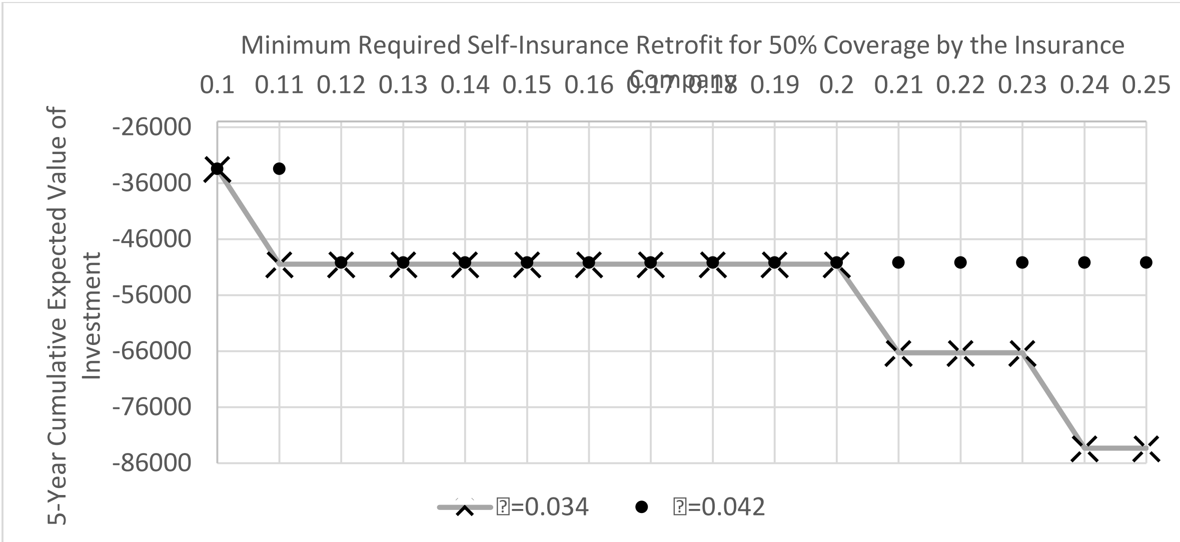

Figure IV-2: Changes in optimal expected value of investment for different amounts of α.

4.5. Case V: Insurance Pricing (M^K)

The price of market insurance premium has a significant impact on the optimal amount of the expected value of investments as well as the investment schedule. Different premium prices were given to the optimization model and optimal values of investments are summarized in Table IV-4.

Table IV-4: Optimal self-insurance investment and market insurance coverage for different premium prices

	Planning Horizon										
$M_{50\%}$	Year 1		Year 2		Year 3		Year 4		Year 5		$\sum_{t=1}^{5} EV^*$
	${I_a}^{1^*}$	C^{1^*}	${I_a}^{2^*}$	C^{2^*}	${I_a}^{3^*}$	C^{3^*}	${I_a}^{4^*}$	C^{4^*}	${I_a}^{5^*}$	C^{5^*}	
$ 1,000	10,000	70%	9,000	90%	100	90%	0	90%	0	90%	-50,450
$ 2,000	5,800	70%	5,800	70%	5,800	90%	1,900	90%	0	90%	-80,301
$ 3,000	5,800	70%	5,800	70%	3,000	90%	3,000	90%	1,700	90%	-92,973
$ 4,000	3,900	50%	3,900	70%	3,900	70%	3,850	70%	3,850	70%	-170,427
$ 5,000	12,000	0%	2,000	50%	2,000	70%	2,000	70%	1,200	70%	-191,680
$ 6,000	12,000	0%	6,000	50%	1,100	50%	0	70%	0	70%	-208,758
$ 7,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-268,914
$ 8,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-271,826
$ 9,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-274,738
$10,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-277,650
$11,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-280,562
1$2,000	12,000	0%	7,100	0%	0	50%	0	50%	0	50%	-283,473

$M_{50\%}$: Premium of the 50% coverage

${I_a}^{t^*}$: Optimal amount obtained for the self-insurance investment

C^{t^*} Optimal coverage obtained given the price of the insurance premium

Results shown in Table IV-4 suggest that as expected, the expected value of the homeowner's investment drops as the price of insurance increases. According to the results, the pattern in optimal investment amount is perceived to be driven by insurance. Homeowners seek to achieve higher insured amount for more years by investing earlier, so that more budget is available for the following years while the contingency constraint is also satisfied earlier. An interesting case is observed when the price of 50% coverage is 4,000 ($M_{50\%}$=$4,000, $M_{70\%}$=$8,000, $M_{90\%}$=$12,000) In this case, the optimal solution is to pay uniformly over the decision period, and purchase 70% coverage for all years except for the first year when the contingency constraint is not satisfied. This result can be explained by the fact that the amount of uniform investment ($3,900) in this case is close to the minimum requirement of investment for 70% coverage ($4,100). Additionally, the minimum investment amount required for 50% coverage ($2,900) is less than the uniform investment amount. As a result, the homeowner can still insure their property, although to a lower extent. Furthermore, the price of 70% coverage ($8,000) plus the uniform investment is within the homeowner's budget (3900+8,000=11,900<12,000).

Besides the case of optimal uniformity in self-insurance, the only affordable coverage (50%) appears in the optimal solution set for the last three years of the planning horizon. In that case, homeowner's best decision would be to forgo of insurance coverage in the first two years and to spend the maximum affordable amount on the self-insurance .As a result, the probability of damage is reduced and coverage eligibility for the following years is satisfied.

5. Summary and Conclusions

The tradeoffs between investments in market insurance and self-insurance in a wildfire prone area were formulated and analyzed in this study. The expected value of the investment was assumed to be the basis for decision making for a rational homeowner with complete information about the risk, prices, and constraints. Mixed integer programing was implemented to find the optimal solution for maximizing the expected value of investment.

It was assumed that the homeowner cannot change the probability of arrival of a wildfire from the forest to the WUI community, but instead homeowners could change the the probability of accruing losses due to wildfire through self-insurance consisting of implementation risk averting activities.

In the numerical example investigated in this study, the main driver of investment was shown to be the availability of insurance; in the absence of mitigation contingency constraint in the market insurance premiums offered in a WUI, the homeowner would spend on insurance only, which is a result of the implicit assumption in the case study setting. When insurance coverage is not offered to a housing area, due to very high risk of wildfire, results showed that the best investment scenario is to pay off the effective treatment plan as soon as the budget constraints allows for it. An accelerating self-insurance investment trend was found to be dominated by uniform expenditures, which itself is dominated by a decelerating investment trend. In other words, delaying the investment on self-insurance activities is not an optimal choice.

Homeowner's resistance towards changing the physical characteristics of their properties through self-insurance risk averting measures was also investigated. A homeowner who is less resistant to implement these measures in their properties may seek higher utility. Additionally, although the expected value of the investment decreases as prices of insurance premiums increase, the optimal trend in investing on self-insurance remains to be the decelerating trend.

This study is one of the first attempts to model the investment of a homeowner on two types of insurance over time and some of limitations are recognized. A major limitation of this investigation is data availability for wildfire-specific insurance coverage in WUI areas. Another limitation is that the risk averseness of the homeowner is not modeled in the expected value of homeowner's insurance investment utility. Although not flawless, the proposed model is able to provide more insight on homeowner's insurance investment decision in a wildfire prone area.

V. From Individual to Community Planning for Wildfire Management

Abstract Wildfire management in the Wildland Urban Interfaces (WUIs), specifically, calls for understanding the nexus between land cover, land use, climate and socio-economic systems. The socio-economic system built on the WUIs is comprised of homeowners, with their major investment at stake: their homes. Recent forest and wildfire management science suggests that a sustainable wildfire management plan is to re-introduce natural wildfire regime on the wildland while protecting WUI community against wildfire damage. Consequently, there is an increasing literature on who is responsible in protecting people in case of upcoming wildfires. While there is not a single answer to this question that fits a wide range of WUI communities, this study suggests a modeling perspective on evaluating the effects of homeowner participation in self-protecting activities including investing on vulnerability mitigating retrofit measures and purchasing insurance. Homeowner's cognitive process about choosing a certain response to the wildfire hazard among available alternatives, have been studied by many researchers and for different communities. However, the integration of the behavior of individual homeowners at the community level and the ability to measure the success of a community in confronting wildfire hazard has received limited attention from the community planning body of research. This study models the effects of individual homeowner's investment decision making on the community's success in minimizing losses due to wildfire events. This study perceives a community as an entity that tries to minimize losses through the investment in appropriate response to a risky situation. The total loss to the community homes is used as the community's success' evaluation measure. The dynamic nature of the homeowner's response to wildfire as well as the spatial interaction of the neighbor parcels during a wildfire event are modeled. The model is dynamic in nature, in that, it accounts for the accumulation of the effects of mitigating retrofit measure over time and its impact on the reducing the probability of damage to wildfires. The model is also a bottom-up or agent-based approach; the interaction between agents is addressed through the impact a burning house has on its adjacent neighbors. The proposed model was applied on a neighborhood of six homes in Santa Fe, New Mexico. The question that is answered by this case study is to find the effects of the combination of the home location and homeowner type on the neighborhood's loss to wildfire. The findings of the case study suggest that the homeowner who has a key role in reducing the neighborhood's loss to wildfire is not necessarily the one who is closer to the forest, but is the one whose property links properties in the Wildland-Urban front to those that are further away from the forest.

Keywords: Wildfire hazard, Vulnerability. Mitigation, Economic Resilience

1. Introduction

The socio-economic systems residing on Wildland Urban Interface (WUIs) communities are highly heterogeneous (Martin, Bender, and Raish 2007). The configuration, setting, and structure of the residential parcels and buildings vary widely within a community, but also the wildfire risk responses decisions made by individual homeowners vary depending on the individual's perception, experience, age, gender, as well as other characteristics. These heterogeneities existing in the WUIs, make it difficult to aggregate a population of homeowners into a single community entity (Martin, Bender, and Raish 2007). On the other hand, in order to enable comparisons between communities and to determine best practices in response to wildfire hazard, proposing a modeling framework for a community in the WUI can be of great value.

In this study an Agent Based Model (ABM) is proposed to evaluate a community's response to wildfire risk considering heterogeneity in the homeowners' attributes and behaviors. The model facilitates the aggregation of the consequences of each agent's behavior on the community's success when confronting wildfire risk and hazard. The model is based on two main assumptions; 1) the homeowners have perfect information about their vulnerability to wildfire, and 2) the homeowners seek optimal investment decisions given their income constraints and the available investment options. The behavior of each homeowner is estimated through two optimization problems: (1) an optimization problem to find minimum cost retrofit measures that reduce the wildfire vulnerability to an accepted level of low or moderate vulnerability compared to high and very high, and (2) an investment schedule optimization problem that attempts to find the homeowner's investment on vulnerability mitigating retrofit measures and insurance over a multi-year period. For each homeowner or agent in the model, the optimal behavior over a pre-set duration is found. Although the optimal solution, especially in the presence of enforcing policies, suggests that homeowners invest on some retrofit activities, some homeowners may be resistant to changing the appearance of their property and land due to its intangible productivity in reducing the property's vulnerability to wildfire. Hence, two types of homeowners are considered in this study. One that only relies on insurance coverage (non-mitigating homeowner), and one that both implements retrofit measures to their properties to reduce wildfire hazard and pays for private insurance (mitigating homeowner). The investment behavior of the homeowners is simulated in a multi-year simulation model considering that homeowners who are willing to undertake mitigation measures, commonly do so in a multi-year basis and not as a one-time decision (Brenkert-Smith et al. 2006; McCaffrey et al. 2011)..

For each year in the simulation, the loss accrued by each homeowner is simulated in a stochastic manner, to consider that when a wildfire occurs it may or may not damage a building. The probability of loss is formulated as a function of the initial vulnerability rating of the home and the cumulative investment on mitigation. The total amount of loss due to wildfire is calculated considering all the properties in the simulation model. Since the occurrence of wildfire and the damage to the properties is of stochastic nature, for each scenario, the multi-year simulation is re-iterated and the damage scenarios are sampled using a Monte-Carlo simulation. The scenarios considered in this study, are different combination of the homeowner type (i.e. mitigating, or non-mitigating).

The spatial impact of neighboring properties on the loss potential of a homeowner is modeled using a conceptual fire spread model based on the Cellular Automation (CA) propagation model. The model is demonstrated using a neighborhood of six parcels in Santa Fe County, New Mexico. The results are in the form of total loss associated with each scenario. Results suggest that the impact of the individual homeowner's decisions' on the community's success in confronting wildfire risk and minimizing community's damage depends on the location of the property. In other words, homeowners decisions cannot be weighed similarly; for example, the homeowner whose property connects properties that are in front of the forest, and hence are first respondents to wildfire, has a much more important role in reducing overall loss to wildfire than the homeowners whose properties are further away from the forest. The losses were higher for a non-mitigating homeowner than for a mitigating homeowner.

2. Background

When protecting their properties, the behaviors of homeowners in the WUI are highly heterogeneous (Martin, Bender, and Raish 2007). Additionally, homeowner's response to wildfire risk impact neighbors through spatial externalities (Butry and Donovan 2008; Cohen 2000; Ayres et al. 2016). Modeling and simulation tools have been utilized to explain or predict the potential financial externalities imposed on neighbors due to possible decisions made by each homeowner. Butry and Donovan (2008) utilized a CA-based fire spread model to account for spatial externalities in mitigation decisions made by homeowners. The externalities were modeled by taking into account the “spillover” or indirect aversion of the damages to a homeowner, which resulted in less number of fire brands reaching the house when fewer neighboring houses are burning because their owners have implemented appropriate retrofit measures to reduce the ignition probability on their properties. They tested 72 scenarios as combinations of spatial arrangements of mitigation projects over the community’s landscape (such as randomly selecting houses as mitigated versus unmitigated, or assuming that mitigating measures are implemented on high risk houses only, versus low risk houses only, etc.), weather conditions represented by the intensity of the burn area (burning of 50% ,70%, or 95% of the unmitigated landscape), homogeneity or heterogeneity of the ignition risk over the landscape, and different effectiveness values assigned to mitigation (10% or 20% reduction in the ignitability of the home due to implementation of mitigation measures). The authors compared the scenarios by measuring the total loss over all homes in the WUI, and concluded that spatial arrangement and concentration of the mitigated area plays the most important role in reducing the total community loss to wildfire. Although the houses and the spatial interactions between them are accounted for in Butry and Donovan (2008)’s model, the homeowner’s decision on mitigation and its variation over time are not considered in their model. Moreover, the variations of home values and mitigation and insurance investments are not taken into account when estimating the total loss to the community.

The investment decision of a homeowner in a decision environment with multiple decision makers has been studied in a few game theoretic models. For example, Amacher, Malik and Haight (2006) proposed a game, between the government and private homeowner, to study the impact of information on the reduction of loss. In their game model, the order of decision making by homeowner and forest manager was shown to be important. Homeowner's optimal decision when interacting with a suppression-oriented forest manager tends to be investing less on mitigation and free riding on the governmental suppression efforts. Two types of homeowners were considered as players in separate games, one of the homeowners was assumed to implement full mitigation and the other was assumed to choose to mitigate partially. As for the reduction in social losses the former homeowner outperformed the latter. Shafran (2008) proposed a game-based model to analyze the behavior of neighbors when confronting wildfire risk taking into account the externalities of wildfire risk. The author assumed that identical homeowners (in terms of income, costs of mitigation, and vulnerability to wildfire) respond to the risk of wildfire by selecting from two options: to invest, or not to invest on making a defensible space around their homes. The spillover effect, the effect of a homeowner's decision on their neighbors (Butry and Donovan 2008) of mitigation was modeled into the reduction of the probability that a wildfire would reach a house and the probability that wildfire can burn a house given that it has reached the vicinity of the house, as a function of the number of homeowners that have decided to invest on mitigation. Through Pareto optimality analysis, they concluded that the optimal community response to wildfire hazard is when at least some homeowners invest on improving the defensible space in their properties. However, the study infers that, if no one else invests on mitigation, there would be no incentive for a homeowner to invest.

Busby et al. (2010) presented a game theoretic model where each player's decision variable was the amount of their mitigation effort, in terms of the level of fuel reduction, . In their model, the liability of the public land manager towards the private homeowner and the vulnerability of the private homeowner were impacted by both players' adopted mitigation strategy Busby, Amacher, and Haight (2013), modeled a dynamic game between two generic land owners as players and included the insurance provider behavior in their modeling. They also accounted for the perception of the private land owner regarding damage from a potential wildfire when there is incomplete information available to the players. The main shortcoming of the available game theoretic models is their inability to consider the heterogeneity among homeowners mainly in terms of their initial vulnerability to wildfire. Additionally, the models are not able to accommodate a large number of players.

Goals and Objectives

In this study, an Agent Based Model (ABM) is proposed to account for the heterogeneity of the agents, multiyear decision making, trade-offs homeowners make when deciding on their response to wildfire hazard through their investments and the spatial externalities between homeowners in case of a wildfire occurrence. ABMs are useful tools for monitoring and enforcing cooperation (Kim and Bearman 1997). Variations in homeowners' response to wildfire risk can be modeled through an ABM. With its ability to accommodate heterogeneity, interactions and adaptation (Heckbert et al. 2010) ABMs have benefited a variety of topics from psychological aspects of social behaviors (Costanza, Fisher, & Ali 2007) to sustainable consumption to natural resource management, land use change (Parker, Manson, & Janssen 2003; Polhill, Parker & Gotts 2008), and urban dynamics (Batty 2005; Batty 2008; Brown & Robinson 2006).

ABM lends itself to policy testing in Urban environment, as Heckbert et al. (2010) note:

"… Cities provide rich territory for research into the Complex relationships between decision making and landscapes affected by human activity. In cities there is a concentration of features that match well with the strengths of ABM: heterogeneity (in house- holds, businesses, neighborhoods, land use); autonomous decision making (e.g., by residents, industry, utilities); direct and indirect interactions (e.g., in property markets, planning and policy); and cross-scale effects (from local development choices to urban expansion) …"

The proposed ABM for studying the success of a community in confronting wildfire is unique in different ways. First and foremost, the proposed model accounts for the heterogeneity in the physical attributes of the property, home values, and the optimal investment plan that homeowners would adopt as their means to respond to wildfire risk. The model uses mathematical models for optimizing homeowner's investment thus addressing one of the missing parts in modeling homeowner's response to wildfire risk. Moreover, the proposed model provides a platform for incorporating spatial attributes of the WUI into the modeling.

3. Proposed Model

ABM builds upon individuals and their behavioral rules, as well as an environment in which or with which the individuals interact (Borshchev and Filipov 2004). The characteristics of a WUI community matches these needs; homeowners, are individuals with predictable behavior, who interact within the residential WUI environment to respond to wildfire hazard.

3.1. Agents' characteristics and goals

In this study, agents are defined as homeowners, and the environment where the agents belong to and interact with is the residential WUI area. Since homeowners care about their utilities in terms of maximum expected value of their investments on wildfire risk mitigation, the agents are of goal seeking type. It is assumed that homeowners have perfect information on the vulnerability of their properties to wildfire as well as the costs of retrofit measures that reduce their vulnerability to wildfire. The level homeowner's vulnerability is pre-defined by wildfire experts. In real cases, Firefighting departments, or other relevant agencies, provide homeowners with an evaluation card for their properties. These evaluation cards indicated building or land elements that make the property susceptible to wildfire damage. As rational agents, homeowners decide between available insurance policies and retrofit measures to increase their compensation after a wildfire occurrence, or to reduce the ex-ante wildfire loss, respectively. Before deciding on the tradeoff between the costs and utility of insurance and retrofit measures, it is reasonable to assume that a rational homeowner seeks for the most cost effective retrofit schedule that yields minimum costs of land/home improvements while achieving acceptable wildfire vulnerability levels.

Retrofit measures in wildfire prone WUIs consists of modifying elements of the land or structure that are susceptible to burn or can transfer the heat of an outdoor fire to the building materials and systems which could result in damage or destruction of the house. In a multi-attribute property vulnerability assessment context, the effectiveness of a retrofit measure in decreasing the vulnerability to wildfire is reflected through the susceptibility rating assigned to the pre-retrofit conditions of the property. The ratings assigned to the elements of a specific property are then added to form the rating score of the property. The total rating assigned to the property is used to define the vulnerability class of the property in qualitative terms such as low, moderate, high, among others. An optimal retrofit plan is the set of retrofit measures that yield minimum cost while ensures the vulnerability rating falls below an acceptable vulnerability class. The cost minimization objective is shown as follows:

$$C_p^* = \min_{x_i} C_p = \sum_{i=1}^{I_p} c_i . x_i \qquad \text{Eq. V-1}$$

Where p denotes the property under investigation, and i denotes an attribute in the feasible retrofit portfolio of the property I_p. c_i is the cost of retrofitting attribute i and $x_i \in \{0,1\}$ is a binary variable for the decision to implement this retrofit measure i (1 if retrofit is implemented for property attribute i, and 0, otherwise).

The optimization constraint is that the new total score of the property p should be less than or equal to the target minimum vulnerability score:

$$\sum_{p=1}^{P_h} \mathrm{s}_i \,.\, (1 - x_i) \le \mathrm{S}^T \qquad \text{Eq. V-2}$$

Where s_i is the score associated with the parcel's rating for index i as indicated on the parcel's evaluation card and, S^T is the minimum acceptable decrease in the vulnerability rating.

$$\mathrm{S}^T = S^a - S_0 \qquad \text{Eq. V-3}$$

Where S^a is the maximum total rating associated with the acceptable vulnerability level and S_0 is the total vulnerability rating of the parcel pre-retrofit. When the homeowner is informed about their optimal retrofit plan with total cost of C_p^*, homeowner mixes between their investment decisions for mitigation and market insurance. Each year, homeowners decide how much to invest to implement mitigation measures on their properties and/or on insurance premiums. Whereas, the investment on mitigation is assumed to be continuous, the insurance coverage options are assumed to be discrete. The investment decision each individual make is isolated from the investments of other individuals. Each year, the amount of investment on physical treatment is constrained to the homeowners' disposable income, which is defined as 10% of the home value, similar to the assumption made in an experimental study by McKee et al (2004). In addition, the total annual amount of investments on treatment and insurance is constrained to 15% of the home value which is an index for affordability (Shan et al. 2016). It is assumed that homeowners are required to keep the vulnerability of their properties at a moderate level over the course of 5 years. Since the initial vulnerability of the homeowners is different, the amount of investment required to achieve a moderate vulnerability rating varies.

For rational homeowners, the optimal annual investments amounts are those that yield the maximum expected value over the planning interval as follows:

$$\max_{{I_m}^t, K^t} \sum_t EV^t = \sum_t \frac{-{I_m}^t - {I_i}^t - p^t . L + p^t \sum_{k=1}^{K} y_k^t . K^t . {e_k}^t}{(1+r)^t} \qquad \text{Eq. V-4} \quad (4)$$

Where EV^t is the expected value of investments at the end of year t, ${I_m}^t$ is the amount of investment on mitigation retrofit measures per year t, ${I_i}^t$is the amount of wildfire specific payment to the insurance company in year t; and p^t is the probability of damage at wildfire season of year t. $y_k^t \in \{0.1\}$ is the binary variable which takes the value of 1 for the selected insurance coverage and zero for other coverage options $\sum_k y_k^t = 1$. The amount of loss incurred due to wildfire and the compensation received from the insurance in year t are represented by L and K^t, respectively. The term r in the denominator is the time value of money factor. Term e_k^t is a binary variable that controls for homeowner's eligibility for chosen coverage, K^t. In hazard-prone areas such as WUIs, insurance companies usually offer mitigation contingent coverage plans. In such cases, the availability of market insurance coverage for wildfire is contingent to the homeowner undertaking a minimum mitigation effort on his property. The test for eligibility is shown Eq. 5:

$$e_k^t = \begin{cases} 1 \quad if \ \sum_{t \in T} \frac{{I_m}^t}{(1+r)} \geq E_k^{Min} \\ 0 \quad\quad Otherwise \end{cases} \qquad \text{Eq. V-5}$$

Where E_k^{Min} is the cost of insurance coverage$k.$. The annual amount of investment on retrofit measures is constrained to a given percentage of the home value that is assumed to be the homeowners' resistance to physical change on their properties in a given year:

$$\forall t \in T: {I_m}^t \leq \alpha.V \qquad \text{Eq. V-6}$$

Where V is the home value, and $\alpha \in [0,1]$ is the maximum annual treatment investment multiplier. In addition to the annual constraint on the self-insurance investment amount, the total annual investment on insurance (both mitigation and insurance) is bound to annual affordable investment cap (I_0):

$$ {I_a}^t + {I_i}^t \leq I_0 \qquad \text{Eq. V-7}$$

Supposing that the homeowner is committed to implement a retrofit plan over the decision interval, there is a minimum amount of cumulative investment on mitigation efforts:

$$\sum_{t \in T} \frac{{I_m}^t}{(1+r)} \geq C_p^* \qquad \text{Eq. V-8}$$

Where C_p^* is the cost of the optimal retrofit plan resulting from the previous optimization (equations 1 to 3). The probability of damage inflicted on the property from a wildfire that has reached the community depends on the mitigation effort undertaken by the homeowner. Adapted from Busby and Arbor (2010) the probability of damage is reduced by the mitigation investment I_m, at a decreasing rate, the inverse of the resilience function used by Busby and Arbor (2010) is used for the estimation of the probability of damage given the investment on mitigation activities:

$$p^t = \frac{\mathrm{A}}{\mathrm{B} + \ln(\sum_{s=1}^{s=t} {I_m}^s)} \qquad \text{Eq. V-9}$$

Where A and B are the adjustable parameters. A typical assumption from prior studies is that when wildfire reaches a building the damage is high enough to be assumed a total destruction (Cohen 2000; Shafran 2008). In this study, it is assumed that the outcome of a wildfire damage is 90% loss of the value of the property:

$$L = 0.9V \qquad \text{Eq. V-10}$$

The compensation a homeowner receives from the insurer is based on the insurance coverage purchased the year of the wildfire. Whereas the amount of investment on physical land treatment is assumed continuous, the choices of insurance plans are assumed discrete.

In other words, there are finite coverage options for homes in the WUI. Homeowner makes decision regarding the self-insurance amount (I_m^t) as well as the coverage option (C^t):

$$K^t = \beta_k V \qquad \text{Eq. V-11}$$

Where β_k, $k \in \{1,2,\dots,K\}$ is the maximum wildfire loss covered by purchasing the insurance coverage option k . The investment on insurance is the price of premium for option k (M_k):

$$I_i{}^t = M_k \qquad \text{Eq. V-12}$$

The optimization problem can be solved using mixed integer programming where the treatment decision variables are of continuous type and the insurance coverage choices are integer. The objective function is non-linear and there are both linear and non-linear constraints.

3.2. Agents' statecharts

State charts can be used to account for the individual homeowner behavior over time. First proposed by David Harel (1987), State charts are micro dynamic models of behavior of an individual agent in ABM. State charts capture different states, transition between states and timing associated with these transitions in the memory of an individual agent (Borshchev and Filiopov 2004). Figure V-1 shows the state chart of each homeowner agent.

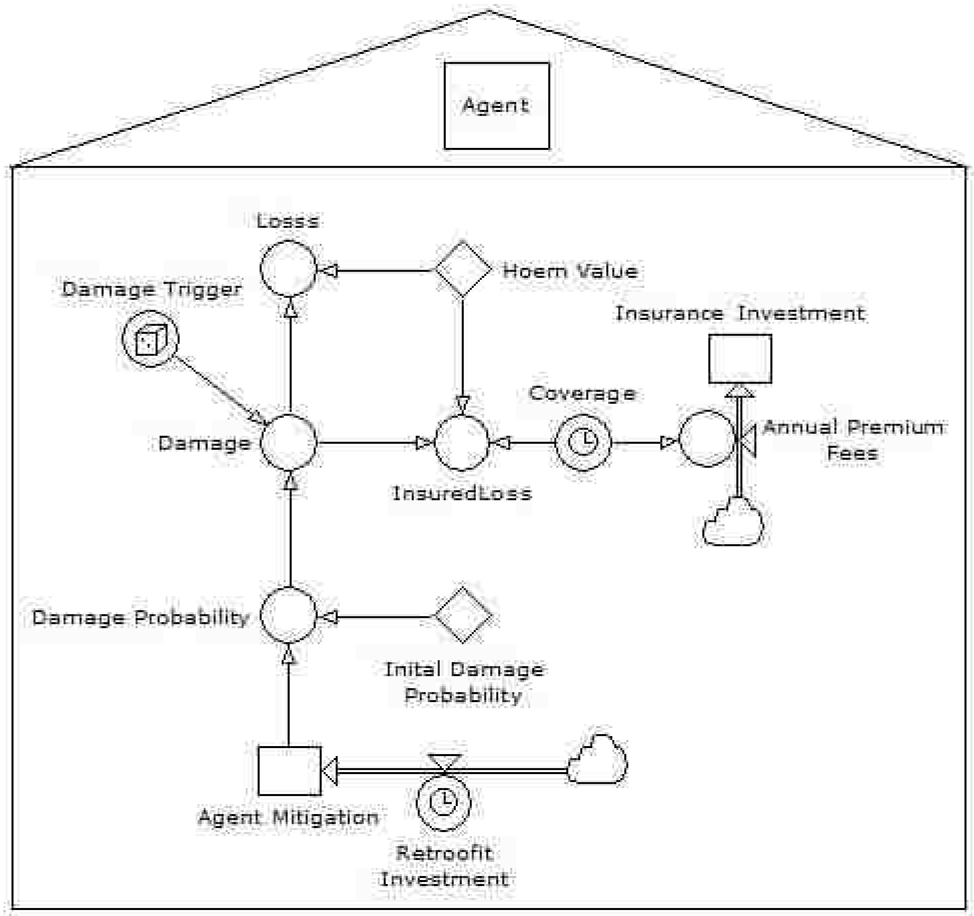

Figure V-1: Statechart associated with a general agent (homeowner).

The initial damage probability shown in Figure 11 is the probability associated with the vulnerability rating of the house. As the homeowner invests on mitigating vulnerability, the probability of damage is reduced. In the proposed model it is possible that fire can happen any year, but it is assumed that the occurrence of wildfire is limited to a maximum of once per year. When the wildfire occurs close enough to the community, it might reach home properties. The probability of damage, as well as the existence of burning homes in the adjacency (will be explained later) would determine whether a house would ignite or not. If the home is burnt due to wildfire, the homeowner would lose 90% of their home value. The loss will be compensated if the homeowner has insurance, and the amount of compensation would depends on the coverage purchased.

The investment on mitigation and insurance is made prior to wildfire season. Wildfire is an exogenous variable in the proposed model. In this model, interactions between homeowners such as information exchange or peer pressure are not considered. However, the indirect interaction between homeowners' properties is considered by increasing the probability of damage to a property when neighbor properties are burning. The probability that a wildfire leads to the damage of a property is calculated by equation 9 independent from the conditions of the neighbor parcels. Then, this probability is multiplied by a factor which is greater than one if the property is adjacent to a parcel that is on fire.

3.3. Spatial interaction between agents

The spatial interaction between neighbors in the case of a wildfire is adapted from Cellular Automaton (CA) simulation. CA is a process oriented simulation which is appropriate for modeling processes that are analogues to fractal growth or diffusion limited aggregation (Batty et al., 1989; Meakin, 1983; Mullins and Sekerka, 1963). The CA-based fire spread model has been applied by Butry and Donovan (2008) to simulate the spread of fires between homes and fuels. CA considers the environment as a mesh of cells that communicate with each other through a system of rules thus facilitating the propagation of a phenomenon.

When the phenomenon is wildfire, the terrestrial attributes of the cells such as elevation, slope, aspect, and fuel content as well as climate data such as temperature and relative humidity defines the probability of fire propagation from one cell to another. However, in this study, the propagation of wildfire is simplified to a great extent since fuel data is very limited on the residential WUIs. The rules applied to this model are:

- Wildfire is originated in the forested and propagates towards residential buildings;
- There is no backward movement for wildfire.
- The probability of burn for homes in the frontline, relative to the forest boundary, is estimated using equation 9
- For homes other than those in the frontline the probability of burn, is impacted not only by the wildfire approaching but also from the neighbor parcels. Burning neighbor parcels increase the probability of burn of the house/. The increase is higher if the neighbor shares an edge than if the neighbor shares a corner in the grid,
- For homes with no active burn in the immediate adjacency, there still exist a probability of attack by embers if there is an active burn within 1 mile from the house. This distance is based on empirical studies for a variety of forest types (Beverly et al. 2010).

As shown in Figure V-2, if a wildfire starts at one edge of neighborhood (in this case on the left side), the houses adjacent to the edge are exposed to wildfire damage first. In the case that any of the houses are exposed to wildfire burn, they act as fuel to wildfire and raise the probability of neighbor properties to get burnt as well. Burning neighbor homes that share a border have a higher impact on raising the probability of ignition of their neighbor properties than those that share a corner.

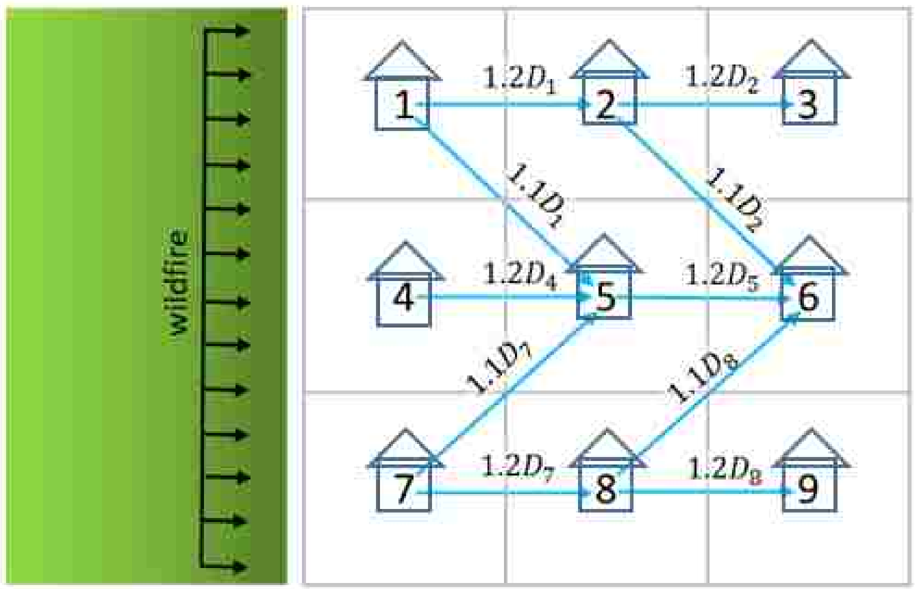

Figure V-2: Spatial Interdependencies, D_h is the binary damage indicator for home h, (1=if home h is burnt and 0 otherwise)

To model the damage occurrence, a random number is generate for each home at each period of time. This random number is compared with the home's updated probability (equation 5), and if the random number is greater, the damage is realized

3.4. Economic Resilience Index for WUI communities

In order to assess the success of community investment throughout the planning timespan, an Economic Resilience Index (ERI) is adapted from Rose (2004); Rose's ERI was originally proposed for individual firms and industries. The index proposed by Rose was, in essence, the percentage of maximum loss to an external shock that is avoided. We extend the use of this index for the WUI community resilience to wildfire as shown in the following:

$$ERI = \frac{Maximum\ Loss - Estimated\ Loss}{Maximum\ Loss} \qquad \text{Eq. V-13}$$

ERI is measured only for those years when a wildfire disaster has occurred.

4. Data collection and model application

To show the collective consequences of homeowners' behaviors when mitigating wildfire, a neighborhood of six parcels is considered as case study, although the scope of modeling can be extended to bigger area. Data on transactions made by homeowners for mitigation or insurance are limited, hence the transactions are assumed to be at the optimal levels resulting from equations 1 to 10. Additional data are obtained for a neighborhood in Santa Fe County, New Mexico. For the nine properties in this case study the optimal cost of mitigation as well as optimal investment schedules are obtained by finding the optimal solutions to optimization models 1 and 4. The estimation of the mitigation and insurance investment is dependent on home values, and their vulnerability level. Vulnerability levels are expressed in scores between 1 and 180. The higher the score, the more vulnerable is the home to wildfire. The Fire Department of the Santa Fe County has conducted a vulnerability assessment for a large number of homes. They defined vulnerability score between 0 and 30, as low vulnerability, between 30 and 60, as moderate vulnerability, between 60 and 90 as high vulnerability, between 90 and 120 as very high vulnerability and beyond 120 as extreme vulnerability. The assessments are based on a multi-attribute rating system that pertains to 25 elements of the land and structure including the roofing system, the type of land cover, the existence of deck, the material of the external wall, among others. Out of the 25 items, 14 are considered feasible retrofit options, Feasibility is defined in terms of the technical or financial feasibility, higly costly items, or impractical items are excluded from the feasible set of items. For example, changing the slope of the parcel is considered unfeasible. Vulnerability classes are low, moderate, high, very high, and extreme and the acceptable level of vulnerability after mitigation is assumed to be at most moderate. The unit costs of each retrofit measure is extracted from RS Means and the National Estimator; the costs of the retrofit measure are then estimated by inputting the estimated quantity of the retrofit work. Quantities are estimated from the plan of the building as well as an aerial photo of the property which are both available at the county's tax assessor's office. The home values necessary to calculate the optimal schedules of insurance and mitigation investment are also obtained from the tax assessor's office of the county. The home values and initial vulnerability scores of the homes, as well as their spatial arrangement relative to the forested land are shown in Figure V-3.

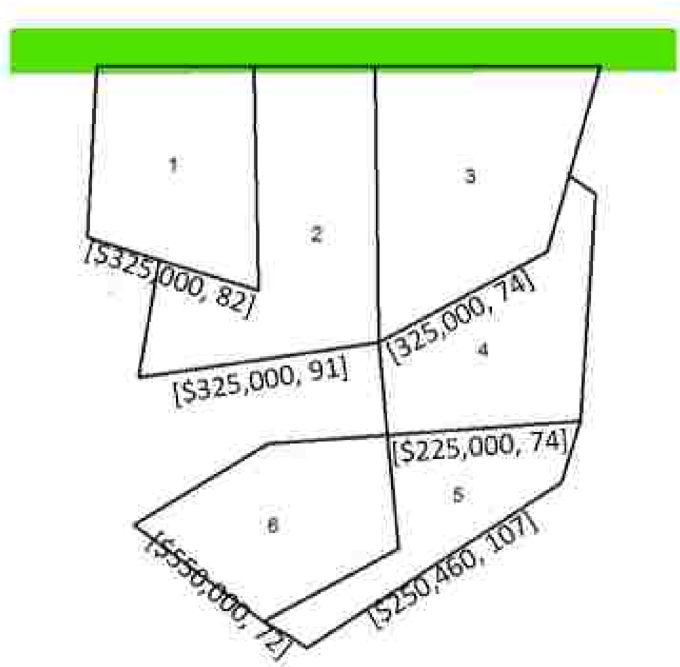

Figure V-3: Value and vulnerability score of the case study homes [value, vulnerability score]

The spatial representation of the agents in Powersim Studio 10 is shown in Figure V-4.

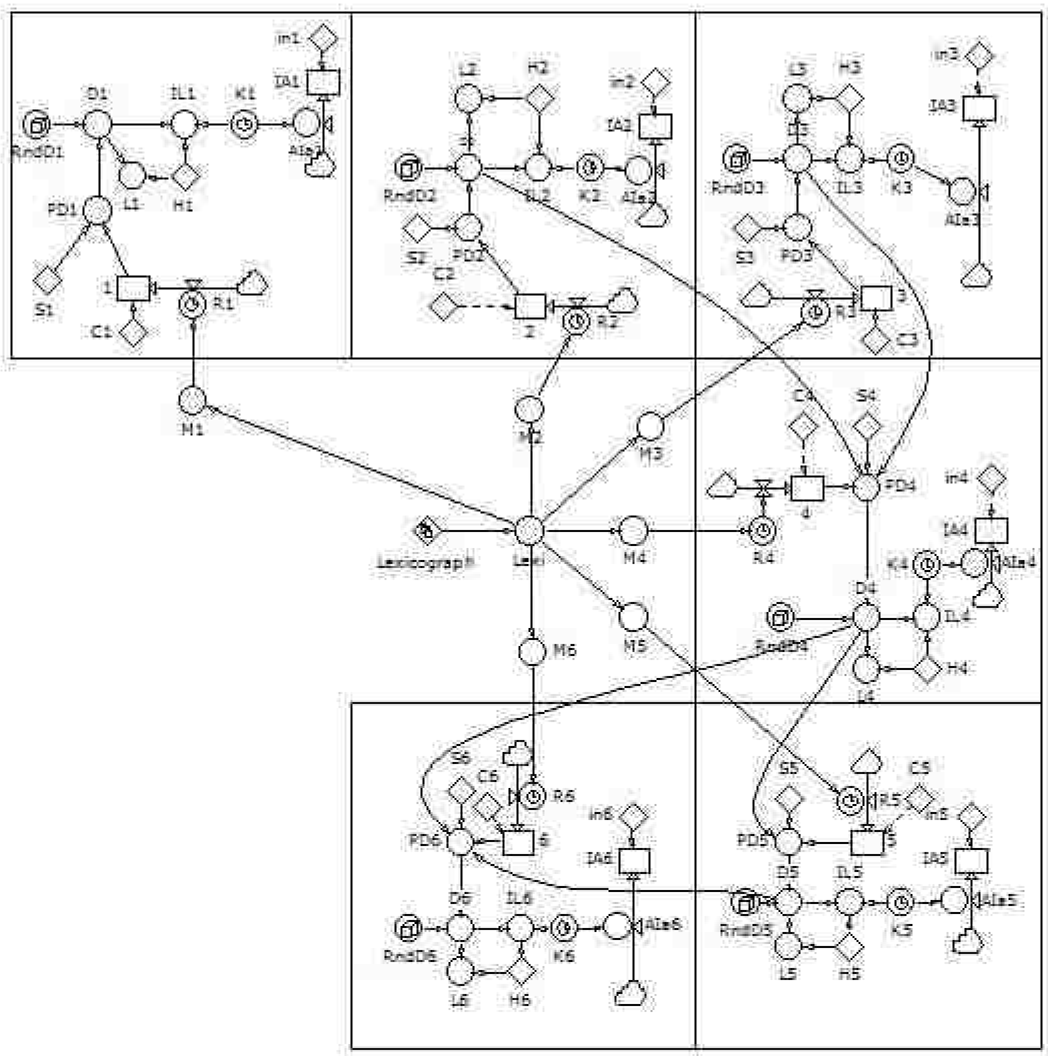

Figure V-4: Agents arrangements and state charts

The state charts of the agents are identical to Figure V-1, except for the use of abbreviated notations. To demonstrate the proposed model, a five-year planning interval is selected. At the end of each year the collective amounts of losses, insured losses, investment on insurance, and investment on mitigation retrofit are calculated and the ER for the year is estimated using equation 10. Since the years in the planning interval are equally susceptible to a wildfire event, the ER is estimated for each year, assuming that every year is the disaster year, in which a wildfire occurs; hence the damage trigger is pulled for all the houses every year, the loss is estimated and the community's ER is calculated using equation 10. The un-insured damage a homeowner incurs is assumed to be 90 percent of the home value following the assumptions made by Shafran (2008) and Cohen (1995) and is equivalent to the the maximum loss in equation 10:

$$Maximum\ Loss = \sum_h 0.9 D_h \quad \text{Eq. V-14}$$

4.1. Scenario testing and results

Scenarios in this study are different composition of homeowners, i.e. which homeowner is of mitigating type and which is not. Since the damage to a property is probabilistic in nature, for each scenario the five-year planning period is simulated and the ER is calculated for each year. The distribution of the ER for each year in any given scenario is then mapped for comparisons and analysis. The optimal investment amounts resulted from solving equations 1 and 4 for the houses are presented in Table V-1.

Table V-1: Optimal investment amount and coverage purchase for the case study homes

					Optimal Investment									
ID	V	S	I_a	P_0	Insurance Coverage					$ Investment on retrofit measures				
					t=1	t=2	t=3	t=4	t=5	t=1	t=2	t=3	t=4	t=5
1	325,000	82	17,000	0.85	70%	90%	90%	90%	90%	7,500	6,000	2,200	1,500	0
2	325,000	91	14,000	0.95	90%	90%	90%	90%	90%	6,200	4,000	3,000	1,000	0
3	325,000	74	10,000	0.75	90%	90%	90%	90%	90%	5,100	5,000	0	0	0

4	225,000	74	6,500	0.75	90%	90%	90%	90%	90%	6,500	0	0	0	0
5	250,460	107	18,000	1.00	70%	90%	90%	90%	90%	6,200	6,000	6,000	0	0
6	550,000	72	10,000	0.75	90%	90%	90%	90%	90%	9,000	1,500	0	0	0

A set of scenarios are generated and compared. The scenarios pertain to the conditions when any combination of homeowners is unwilling to implement mitigation retrofit measures on their properties and to see its effect on the ER. For a neighborhood with six neighbors there are 2^6=64 independent scenarios of homeowners' participation in investment. To generate all scenarios a lexicographic permutation generator (see Bauslaugh and Ruskey 1990) for a set with 6 members is used. Each permutation is a six-dimensional vector with binary component. When the component associated with an agent is zero, it means that the homeowner will not implement retrofit measures for their property. The lexicographically generated scenarios are shown in Figure V-5. For example, the 4th scenario in Figure 19, shows that homeowners five and six, as shown in Figure V-3, are mitigating and the others are not.

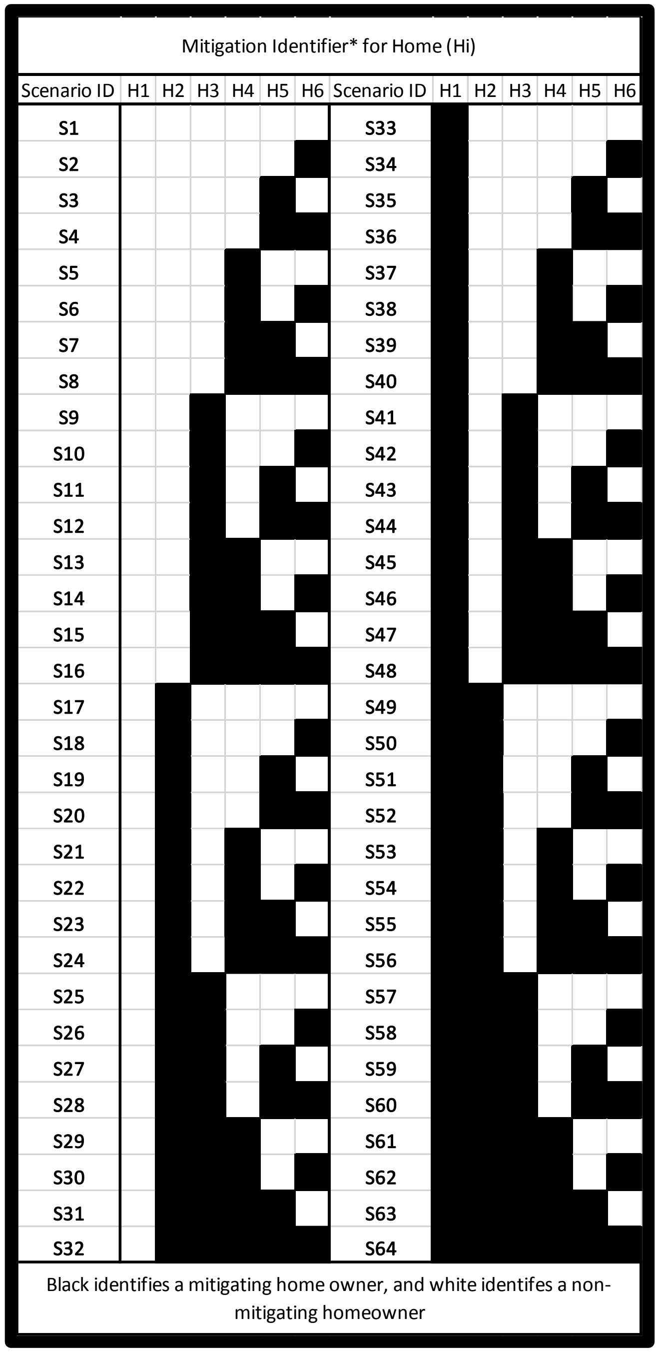

Figure V-5: Scenarios generated by lexicographic permutation generator

The proposed model is written and run in Powersim Studio 10. To iterate the stochastic simulation, the Risk Analysis tool in Powersim is used. The tool allows for iterating the multi-period simulation for many times (up to 10,000). To ensure running all scenarios for equal number of times, the number of iterations is set to 3,200 (=64*50), where 64 is the number of scenarios and 50 is the number of simulation runs for each scenario. The iteration index is then used to call for the scenarios as shown in the following equation:

$$Scenario\ i: S_i = S_{iteration - \left[\frac{iteration}{64}\right] \times 64} \quad \text{Eq. V-15}$$

Where $iteration$ denotes the Risk Analysis tool's iteration and bracket ([]) denotes the floor integer of the fraction. The scenario that is called for is then input to the model as a mitigation multiplier array as shown in the following:

$$I_a{}^{scenario} = M^{scenario}. I_a \qquad \text{Eq. V-16}$$

Where I_a is the matrix (5 by 6) of annual investment plan for mitigation and M^s is a (6 by 1) vector of binary variables associated with the specific $scenario$. The section of the simulation that calls for the scenarios is shown in Figure V-6:

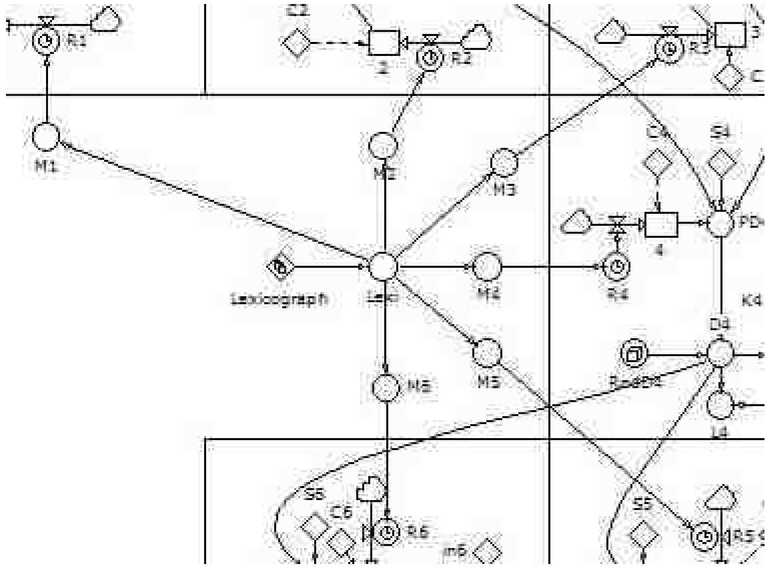

Figure V-6: Calling for scenarios

The number total loss values estimated for the iterations of the simulation at the end of the fifth year, when all the mitigation investment is made, is finite. Values are shown in Table V-2.

Table V-2: Estimated loss values and theirs associated index

Loss ID	Total Loss Value	Loss ID	Total Loss Value
L1	$495,000	L9	$1,215,414
L2	$697,500	L10	$1,282,500
L3	$720,414	L11	$1,305,414
L4	$787,500	L12	$1,372,500
L5	$922,914	L13	$1,507,914
L6	$990,000	L14	$1,575,000
L7	$1,012,914	L15	$1,597,914
L8	$1,080,000	L16	$1,800,414

The number of occurrences of the loss values shown in Table V-2for each scenario is graphed in the bar chart shown in Figure V-7. The loss values are color coded with darker colors associated with higher loss amounts.

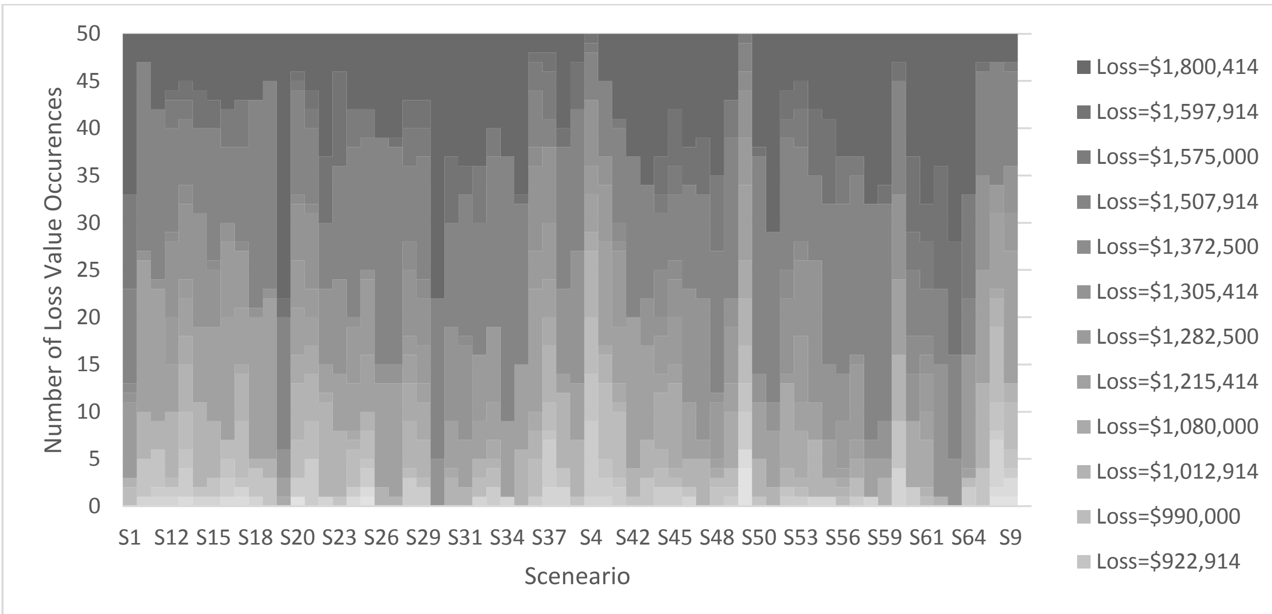

Figure V-7: Total loss value occurrence for scenarios (S_i).

As shown in Figure V-7, The X axis shows the scenarios described in Table V-2; The Y axis, is the number of times (out of 50 iterations of each scenario) that the loss type (L_j) as described in Table 3 has occurred. Since the losses are coded by the relative intensity of the shade of gray, when the column associated with a scenario is generally darker, it is expected that the scenario results in higher losses. There are four scenarios that are composed of mainly dark-colored vertical segments which can be inferred as those scenarios resulted in worse results, (i.e. higher loss value) compared to others. These worse scenarios are S1, S2, S3, and S63. The mitigation plans associated with these scenarios are shown in Table V-3.

Table V-3: Scenarios with highest loss values for the neighborhood

Scenario ID	Does Homeowner 1 mitigate?	Does Homeowner 2 mitigate?	Does Homeowner 3 mitigate?	Does Homeowner 4 mitigate?	Does Homeowner 5 mitigate?	Does Homeowner 6 mitigate?
S1	No	No	No	No	No	No
S2	No	No	No	No	No	Yes
S3	No	No	No	No	Yes	No
S63	Yes	Yes	Yes	Yes	Yes	No

As is shown in Table IV-4, aside from the case where no one implements mitigation measures the next two worst scenarios are for the cases when the three homes in front of the wildland, as well as the 4^{th} home that transfer the damage probability to the two homes in the back are not mitigating their risk. The third scenario is for the case when the owner of the most expensive home decides not to mitigate and despite everyone else mitigating, when the most expensive house burns the total loss will increase. In comparison, the best scenarios (the lighter vertical lines in Figure V-7) are S4, S5, and S6, shown in Table V-4.

Table V-4. Scenarios with least loss

Scenario ID	Does Homeowner 1 mitigate?	Does Homeowner 2 mitigate?	Does Homeowner 3 mitigate?	Does Homeowner 4 mitigate?	Does Homeowner 5 mitigate?	Does Homeowner 6 mitigate?
S4	No	No	No	No	Yes	No
S5	No	No	No	No	Yes	Yes

S6	No	No	No	Yes	No	No

The best scenarios pertain Homeowners 4, 5, and 6 are of mitigating type. The mitigation of these houses can be interpreted as mitigating the probability that the most expensive house burns in a wildfire, i.e. vulnerability of the homes to wildfire. The simulation setting also allows testing externalities in wildfire mitigation by homeowners. For this purpose, the spatial externality is defined as the damage to a property due to a burning neighbor property. The following equation formulates externalities represented in the simulation results:

$$\text{E}xternality = \begin{cases} 1 & if\ (r > P(D))\ And\ (D = 1) \\ 0 & otherwise \end{cases} \qquad \text{Eq. V-17}$$

The situation when the damage trigger (r) does not result in wildfire damage by itself, but when the probability is magnified by the burning neighbor parcels (10% from a neighbor that shares a corner with the subject property, and 20% from the neighbors that share an edge of the parcel). In the case study, because properties number 4, 5, and 6 can are not in the frontline relative to the forestland (as shown in Figure V-3), their probability of damage may be magnified by their neighbor parcels and hence will burn due to spatial externality . The results show that out of 16,000 iterations, (16,000 = 64×50×5) 2125 times the externality was the primary reason of damage to house #4, 601 times for house number 5 and 6,118 times for house number 6. Although the investment on insurance was kept constant between scenarios, the average amount of investment for achieving different ER values is graphed in Figure V-8.

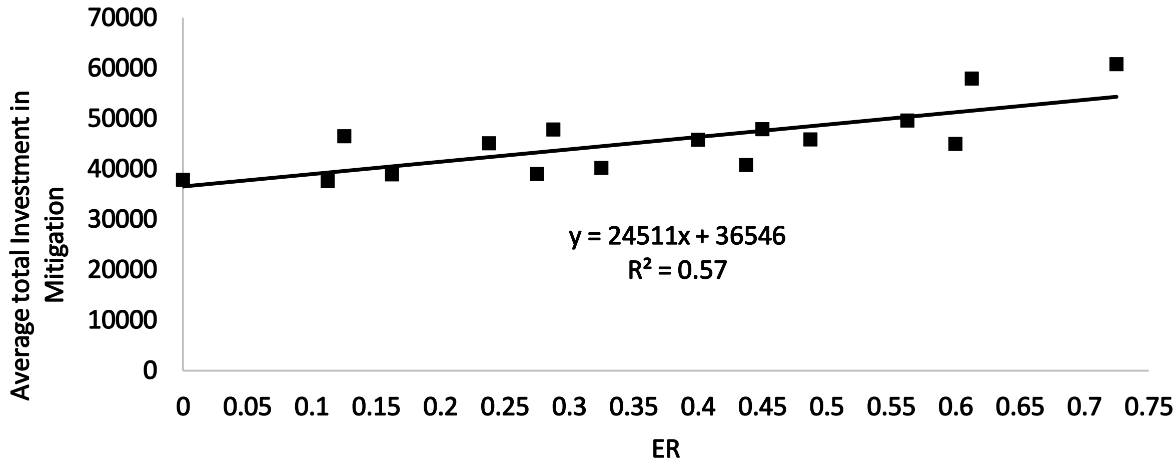

Figure V-8: Average investment amount estimated for obtained ER values

As shown in Figure V-8, higher values of ER require higher mitigation investment. The increase in the amount of investment require to achieve the maximum economic resilience index is $23k.

5. Conclusion

An Agent Based Model (ABM) is proposed to simulate the spatio-economic system on a neighborhood in a Wildland Urban Interface (WUI). The model offers many contributions and benefits. First and foremost, the model allows for a fine scale modeling resolution in which the agents of the model are the homes and their owners. The spatial externalities between the houses are modeled and measured as well. The model builds on the assumption of homeowner rationality. A homeowner that is willing to implement mitigation measures on their properties, would optimize their annual investment amount in a tradeoff with their investment on insurance and over their wildfire mitigation planning period. So, the investment on mitigation is either optimal or zero in the case of a homeowner unwilling to undertake mitigation activities. The minimum total mitigation investment necessary to lower the structural ignitability index from high or very high to moderate or low ignitability is estimated through the cost estimation of retrofit measures. The optimal retrofit plan is found through the implementation of integer programming. As for the optimal amount of annual investment on the mitigation, a mixed-integer programming model is proposed and solved considering affordability constraints. Given the optimal retrofit plan and the annual investment amount the agents are put in the context of a neighborhood in a WUI community. The spatial externalities are represented in terms of magnification in burn probability of houses when one or some of their neighbor properties are burning. A case study is solved to show the applicability of the model. The results of the model confirm the spatio-economic nature of the WUI neighborhood under study. This spatio-economic system is analyzed through the testing of all combinations of the neighbors' willingness or unwillingness to implement wildfire mitigation activities on their properties. In the analyzed case study, the highest losses were attributed to the cases where the threat to the most expensive property was heightened either due to homeowner's unwillingness to mitigate or burning neighbor properties. The number of times a house was burnt due to the spatial externality issues was also measured using the simulation results, which provides an useful tool to improve policy research in this regard. In addition, the results of the stochastic simulation iterations show that a higher economic resilience index could be achieved by higher mitigation investment. The efficiency of investments in mitigation in increasing the economic resilience ($\frac{\partial ER}{\partial\ Investment}$) was estimated at 1/24,511 ($\$^{-1}$).There are a few limitations to this study. The number of homes in the neighborhood is relatively small, and may not represent a real WUI community. In addition, the wildfire simulation module used in this study is relatively simple with some unrealistic assumptions about wildfire dynamics. The investment amount on mitigation is assumed to be either zero or optimal which may eliminates the investment amounts in between. Future work for this study will be to improve such limitations. The mitigation investment will be modeled so that instead of choosing the investment amounts, the homeowner can choose which mitigation measures, among a list of possible items, they'd want to choose in order to reduce the vulnerability of their homes to wildfire.

VI. Conclusion

This dissertation focuses on improving the state of science and practice regarding wildfire mitigation in the Wildland Urban Interfaces (WUIs). The objectives described in Section 1.2 were achieved by integrating different analytical and simulation tools which included: Hedonic Pricing Method, Integer programing, Monte-Carlo Simulation, Agent Based Model, Ordinary Least Squared (OLS) regression model.

6.1 Summary of Research and Conclusions

Chapter 2 proposed a HPM to decompose the impact of wildfire on housing values in the WUI. This investigation explored the complex relationship between wildfire and housing values in a WUI community with significant past experience with a catastrophic wildfire disaster, Los Alamos, New Mexico. The case study landscape has a large, noticeable burn scar, and a significant need for the reduction of hazardous fuels in the larger forestland. Thus, this WUI community exhibits indicators of both ex-ante risk and ex post damage. Viewed through the lens of social learning (Cutter et al. 2008), the housing market was investigated as a possible indicator of community adaptation or responsiveness to wildfire risk. If a community experiences a significant damage event, would it make them more sensitive or responsive to ex-ante risk, especially when the damage event is still highly salient with a visible burn scar?

Spatial econometric results show that, as expected, the visual disamenity of the fire scar negatively impacts property values, lowering the value of the average house in our sample by approximately 2.5 percent. However, even with this evidence -- a visual and monetary reminder of the negative consequences of wildfire, wildfire risk is not negatively capitalized into housing values. Rather, ex-ante wildfire risk has a positive effect on housing prices (0.3 percent for the average house). While inconsistent with social learning in a fire-adapted community, this result is consistent with the wildfire risk mitigation paradox. Hence mitigation efforts by homeowners may be inadequate.

Chapter 2 proposed a retrofit cost optimization for reducing residential vulnerability to wildfires. Integer programing was used to find the optimal combination of retrofit activities that led to the minimum total cost of vulnerability mitigation. A cost model was derived for wildfire retrofit planning for residential properties based on building's area and initial vulnerability rating of properties. The resulting cost model suggests that for an average property in the study area, an extra unit of vulnerability rating adds 119 dollars to the minimum retrofit costs.

Chapter 3 investigated the investment decisions made by homeowners in WUI areas when confronting wildfire risk and loss. An investment schedule including both market insurance and self-insurance was subject to an optimization problem with the objective of maximizing the expected value of homeowner's investments to decode the reasons behind revealed preferences of WUI homeowners. To deliver this objective the investment decision of homeowners over a multi-year investment plan was modeled considering the effects of budget and market insurance policy constraints. Using a mixed-integer programming, the optimal annual investment for market and self-insurance were derived.

In the numerical example investigated, the main driver of investment was shown to be the availability and governing conditions of the insurance market in the WUI of interest. The results, suggested that in the absence of mitigation contingency constraint in the market insurance premiums offered in a WUI, a homeowner would invest on market insurance only. When insurance coverage is not offered for a housing area, due to a very high risk of wildfire, results showed that the best investment scenario is to invest completely on self-insuring retrofit measures considering budget constraints. An accelerating self-insurance investment trend was found to be dominated by uniform expenditures, which itself is dominated by a decelerating investment trend. In other words, delaying the investment on self-insurance activities is not an optimal choice. Homeowner's resistance towards changing the physical characteristics of their properties through self-insurance risk averting measures was also investigated in this study. A homeowner who is less resistant to implement these measures on their properties, and may allow for physical changes to the appearance of their properties, would seek higher expected value of investment compared to a homeowner who is resistant to change. Additionally, although the expected value of the investment decreases as prices of insurance premiums increase, the optimal trend when investing on self-insurance remains to be the decelerating trend.

In Chapter 4, an Agent Based Model (ABM) was proposed to account for: (1) the heterogeneity of homeowners in a WUI, (2) multiyear decision making, (3) trade-offs homeowners make when deciding on their response to wildfire hazard through their investments and, (4) the spatial externalities between homeowners in case of a wildfire occurrence.

For each year in the simulation, the loss accrued on each homeowner was simulated in a stochastic manner, in that, when a wildfire occurs it may or may not damage a building. The probability of loss is formulated as a function of the initial vulnerability rating of the home and the cumulative investment on mitigating activities on the property. The total amount of loss due to wildfire is summed over all the properties in the simulation model in order to reflect the collective consequence of homeowners' response to wildfire risk and damage. Since the occurrence of wildfire and the damage to the properties is of stochastic nature, for each scenario, the multi-year, the proposed simulation is re-iterated and damage scenarios are sampled using a Monte-Carlo simulation. The scenario of interest in this research, was the composition of the WUI homeowners in terms of their response to wildfire risk (i.e. mitigating, or non-mitigating).

The spatial impact of neighboring properties on the loss potential of a homeowner was modeled using a conceptual fire spread model based on the Cellular Automation (CA) propagation model. The model is demonstrated using a neighborhood of six parcels in Santa Fe County, New Mexico. The results are in the form of total loss associated with each scenario (i.e. community composition). As the results suggest, the impact of a specific type of homeowners can be amplified by the spatial composition of their homes. For example, we found that the crucial role is for the homeowner whose property connects properties that are in front of the forest, and hence are first respondents to wildfire, to those that are further away from the forest. In cases where that specific homeowner was of non-mitigating type, the losses were higher than when he was of mitigating type.

6.2 Limitations and Future Research

One of the main limitations in Chapter 1 is the use of assessed home values compared to the sales value of homes. This limitation will remain as long as New Mexico remains a non-disclosure state. Another limitation is that the size of fuel layer's unit used for calculation of risk is coarse compared to the scale of residential properties. This is a data availability limitation that can be improved by using high-resolution LiDAR imagery data.

When developing the cost model for optimum retrofitting measures, it was assumed that there was no correlation between the impacts of implementing two retrofit measures which leads to an overestimation of the costs of retrofitting and favors a more cautionary retrofit decision. However, in order to reach the lowest cost of implementing retrofit measures, the correlation between different retrofit measures should be considered. Another limitation was the lack of accuracy when estimating the amount of work for some of the retrofit measures, which could be improved by using LiDAR remote sensing methods. The cost data could vary between communities, and as a result, the parameters of the cost function, and the optimal cost range changes would vary as well. However, the suggested framework is flexible and could be implemented in different communities, and also for other types of natural hazards. Even though homeowner preferences in post-retrofit mode (material and or design) of the land and building element were considered in this study, accurate information on homeowner's preferences could reduce the uncertainties involved in estimation of unit costs of retrofit measures and help improving the model's accuracy. In communities that are required to have a Community Wildfire Protection Plan (CWPP), reassessments take place for updating the CWPP. The difference between the evaluation cards associated with consecutive assessments carry information on homeowners' preferences when selecting from the retrofit measures. Moreover, surveying homeowners is a direct approach to understanding homeowner preferences.

When evaluating the optimum investment schedules considering self-insurance and private insurance, data for wildfire-specific insurance coverage in WUI areas was unavailable. Another limitation of this study that could be considered for future research is the consideration of risk averseness of the homeowner in the expected value of homeowner's insurance investment utility. The proposed model, however, is able to provide insight on homeowner's insurance investment decision in wildfire prone areas.

A crucial limitation in the proposed ABM, is that agents do not update their strategies based on prior model time periods. The model employs preset strategy sets for homeowners, and once a homeowner picked a strategy it cannot be changed, which is unrealistic. Another major limitation of this study is that the effect of initial conditions on the results was not evaluated. The quality of this model will be improved in the future by linking the model with stated and revealed preferences of actual homeowners.

6.3 Research Contributions to the Body of Knowledge

This study improves the existing literature of HPM for wildfire risk and damage analysis, by accounting for wildfire risk and damage simultaneously. In addition, by adopting more rigorous measures of wildfire damage and risk for measuring the impacts of wildfire on the housing market, this study suggests instrumental improvements in applying HPM for wildfire risk and damage analysis. The damage measure was improved by using the extent of view of each home on a previous wildfire burn scar, compared to previous practice that used view/no-view binary variable in the analysis. The risk measure is improved by using a sophisticated measure of crown fire potential map that uses multiple attributes, wind, land slope, aspect, and vegetation, compared to the previous literature that accounted for vegetation as the only indicator of wildfire risk.

This research offers a few contributions to the state of science and practice of civil engineering. First, unlike flooding, seismic and hurricane hazards, the vulnerability of the built environment to wildfire has not captured adequate attention from the civil engineering body of research; and as a result one contribution of this research is to promote the importance of decision making regarding wildfire hazard and residential vulnerability to wildfire. Second, although wildfire is of specific interest to the authors, the methodology proposed in this research is innovative in the context of retrofit planning for a large number of buildings in a community. The proposed framework generates an added value to the tax appraisal surveys that are collected on annual basis by incorporating them for estimating the amount of work required to implement each retrofit measure. In addition, using multi-attribute vulnerability assessments, although less rigorous compared to more quantitative approaches, facilitates optimization of retrofit plans for a large number of buildings. Computationally, the hybrid optimization and Monte Carlo simulation suggested in this research shows the potential of the proposed framework for application to large communities adding a valuable information to the community planning decision making process.

The suggested functional form for modeling cost of an optimal retrofit plan is unique in the sense that it takes into account actual behavior of a cost function as it is an economic production function in nature. Busby and Albers (2010) argue that investment required to increase resilience (equivalent to decreasing vulnerability) should be concave in the initial resilience (vulnerability). In other words, the amount of investment required to decrease vulnerability increases in the amount of initial vulnerability by a decreasing rate. In addition, an interaction term between initial vulnerability and the area of the building is suggested to reflect the interaction between the two, since the marginal cost of vulnerability is a function of area and the initial vulnerability of the property.

This study is also one of the first attempts to model the investment of a homeowner on two types of insurance over time. The problem to be addressed is stated as a dynamic optimization, which is to find what an optimal investment trend is, and why some investment behaviors are more popular than others. The investment trend and insurance constraints are imposed to study the homeowner behavior in investing on wildfire risk. The model is able to answer why in the absence of self-insurance enforcement through the eligibility constraint for market insurance, one would only invest on market insurance. In addition, homeowner preference for time trend of the investment is model, and it is shown that it is more optimal to invest more in the beginning of the planning interval than at the end of the planning interval.

The ABM model offers many contributions and benefits. First and foremost, the model allows for a fine scale modeling resolution; the agents of the model are the homes and their owners. The spatial externalities between the houses (the fact that a house burns because a neighbor house is burning, otherwise it would burn) are modeled and measured as well. The model builds on the assumption of homeowner rationality. In other words, a homeowner that is willing to implement mitigation measures on their properties, would optimize their annual investment amount in a tradeoff with their investment on insurance and over their planning period. Spatial externalities are represented in terms of magnification in burn probability of houses given one or more of their neighbor properties are burning.

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