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A Systematic Investigation of the effect of wildfire events and risks on property values

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To my husband, Renbin, and my two beautiful daughters, Aima and Anna, without whom this would not have been possible.

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ABSTRACT

Wildfires frequency and severity have been increasing in the western United States over the past few decades. This rising threat is caused by the accumulated fuel load, climate change, and the rapid expansion of housing in the wildland-urban interface (WUI). Since most mitigation and suppression costs are borne by taxpayers, policy analysts seek both market (e.g., protection and suppression cost) and non-market cost estimates of wildfires. As one tool, the hedonic pricing method is commonly used to investigate wildfire effects on property values. There are a variety of hedonic studies investigating wildfire, with mixed and/or inconsistent results. Model estimates are further complicated by a variety of data availability issues as well as varied econometric modeling decisions made by analysts.

This analysis applies spatial econometrics modeling strategies in a hedonic pricing model framework to examine the joint effect of both past fire occurrence and current risk on property values in Santa Fe County, New Mexico. The objective of this analysis is twofold. First, I systematically investigate wildfire effects on property values via the hedonic model using a variety of modeling approaches, including varying or alternative measures for property values, wildfire event and risk, and econometric modeling techniques. Secondly, using hedonic results as primary estimates, I then investigate how the effect of wildfire varies with data availability and econometric modeling techniques through internal meta-analysis.

The systematic investigation can be grouped and classified as measures for property values, wildfire occurrence and risk (which capture data availability issues), or econometric modeling techniques (which capture subjective modeling decisions of the analyst). The systematic investigation includes: two dependent variables (estimated sale price and assessed property value); two measures for wildfire events (the nearest fire measure and the aggregate fire measure with 4 buffer zones), each with two time frames (7 year and 15 year); three risk measures (GIS-based composite hazard and risk assessment, WUI risk assessment and individual-level house risk assessment); two commonly-used hedonic functional forms (semi-log and double-log); and four spatial dependency approaches (independent, spatial lag, spatial error, general spatial model), with three weight matrix. Overall, variations in data and econometric specification produce 2,000 regression results for hedonic model.

Summarizing the direction of wildfire estimates, I find that past wildfire events/occurrences have a negative effect on property value. Specifically, the marginal implicit price (MIP) for a one kilometer increase in distance from the nearest fire $3,461 (in 2013 dollars), implying an increase in assessed value of 1.1%. The MIP for one additional burn near the house is $14,375 (in 2013 dollars), implying a decrease in assessed value of 4.6%.

Secondly, the effects of risk on property value vary by risk measure, risk level, and geographic area. For composite risk and WUI risk, wildfire risk increases property values below a certain risk level and the relationship tends to be negative or insignificant once risk reaches that threshold; for house level risk it reduces property value. The effects of wildfire risk also differ across Non-WUI and WUI. In the Non-WUI area, the positive effects of amenity dominate, and thus wildfire risks tend to increase property value. However in the WUI the negative effects of wildfire risk offset, or even exceed the positive effects of amenities, resulting in a non-significant or negative relationship.

Further, meta-analysis reveals the following results. First, models that use assessed value data give higher R^2 than models that use estimated sales price data. The assessed value models also lead to more significant estimates and larger MIP estimates. Secondly, ignoring spatial autocorrelation either leads to overestimate of MIP or has no significant effect on MIP estimates. Third, the measurements of wildfire risk significantly influence effects of past wildfire events on property value. This reveals the importance of joint estimation of both wildfire events and wildfire risks. Ignoring the effects of wildfire risk in hedonic models might result in inappropriate estimates.

Overall, this analysis systematically investigates the effect of past fire occurrence and current risk on housing prices, using a variety of data measures and modeling techniques. Different from previous studies, which only present “the best fit model”, this analysis conducts 2,000 hedonic regressions on wildfire effects, and then examines how judgements and choices made by researchers affect wildfire effects on property values. This approach synthesizes results of hedonic models in a concise and structured way, but also improves the robustness and reliability of our results in ways that are useful for informing policy recommendations.

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Chapter 1 Introduction

1.1 Background: the growing wildfire threat

Wildfires have burned an increasing large areas in the United States (US), with the annual area burned reaching its highest level (4 million ha) in 2015 (National Interagency Fire Center, 2015a). Wildfires in the West have increased in frequency, size and severity over the past few decades (Anthony L. Westerling, Hidalgo, Cayan, & Swetnam, 2006; Littell, McKenzie, Peterson, & Westerling, 2009; Jay D. Miller, Safford, Crimmins, & Thode, 2009; Dillon et al., 2011; J. D. Miller, Skinner, Safford, Knapp, & Ramirez, 2012). There is an increasing trend in the occurrence of large fires (> 405 ha) with greater burn areas from 1984 to 2011 in the western US. Large fires are increasing at a rate of seven additional fires per year. The average area of the burn increases by 355 square meters annually, on average (Dennison, Brewer, Arnold, & Moritz, 2014). A regional study of high-severity fires found the percentage of high-severity fires in Nevada and California increased significantly from1984 to 2010, as did the size of the areas burned by high-severity fires (Jay D. Miller & Safford, 2012).

Past fire suppression policies and climate change are considered to be important drivers of the increasingly severe wildfire situation. Over the past century, the implementation of aggressive fire suppression policies impeded the role of fire as an ecological process that reduces fuel load (Keane et al., 2002). These suppression policies therefore contribute to “unnatural fuel buildup” (Brown, 1983), which in turn results in larger and more severe wildfires in recent years (Arno & Brown, 1991; PiñOl, Beven, & Viegas, 2005; Donovan & Brown, 2007; Keane et al., 2009). Climate change also has an impact on fire activities through the creation of warmer and drier conditions. This creates longer fire seasons, increased fuel loads; climate change has also increased the frequency of lightning (National Wildfire Federation, 2008). Wildlands are more likely to experience fires when there are the contributing factors of high spring and summer temperatures, and earlier snowmelt (Anthony L. Westerling et al., 2006; P. Morgan, Heyerdahl, & Gibson, 2008; Anthony LeRoy Westerling, 2016). Littell et al. (2009) found that climate change explains 33 to 87 percent of the variation in area burned in the western US from 1977 to 2003.

Furthermore, the wildfire threat is projected to increase as climate change continues (P. Morgan et al., 2008; Littell et al., 2010; Hurteau, Bradford, Fulé, Taylor, & Martin, 2014). Warmer temperatures and drier conditions predict higher fire potential, longer fire seasons and more frequent fires throughout the summer and autumn (Liu, Goodrick, & Stanturf, 2013). The growth of the wildland-urban interface (WUI) has also been thought to contribute to the increased threat of wildfires. According to a Blue Ribbon Panel Report, of the 17 million new homes built from 1990 to 2008, 10 million (59%) were constructed in fire-prone areas (International Code Council, 2008). Only 34% of the WUI was developed by 2008; the remaining 66% is projected to be developed at a rate of 2 million acres a year (International Code Council, 2008). In 2010, the WUI covered an area of 771,000 square kilometers, making up 10% of conterminous land in the US. Approximately 44 million houses are located in the WUI, with 98 million inhabitants, accounting for 34% of households and 32% of the total population (Martinuzzi et al., 2015). Moreover, according to a Forests and Rangelands report in 2009, approximately 70,000 communities in the US are at risk of exposure to wildfire. Of these communities, fewer than 8% have a Community Wildfire Protection Plan (CWPP) (Forests and Rangelands, 2009).

Taken together, wildfire protection and suppression costs have risen substantially. In the 1990s, the average annual cost for suppression was less than $1 billion; it exceeded that figure for the first time in 2000. Since then, the average annual fire suppression expenditures have risen some 40% to $1.4 billion (National Interagency Fire Center, 2015b). Suppression costs are expected to continue to rise, reaching $1.8 billion in 2025 (US Department of Agriculture, 2015). Further, the rising cost of firefighting is placing an ever-increasing burden on the Forest Service's budget. In 1995 its share of the budget was 16%; by 2015 it had ballooned to more than 50% (US Department of Agriculture, 2015). Making matters worse, the reported suppression costs capture only a relatively small proportion of the full cost. Hall (2014) estimated the cost of wildfires in the United States in 2011 amounted to $329 billion, which includes "the losses caused by fire and the money spent on fire prevention, protection and mitigation to prevent worse losses, by preventing them, containing them, detecting them quickly, and suppressing them effectively". Although this estimation is larger than estimates from US Department of Agriculture, it still does not capture the full cost of wildfire (e.g., health impact).

The rising firefighting appropriations limit the resources allocated to non-fire programs of the Forest Service. For example, from 2001 to 2015, the rising cost of fire has caused a 24% reduction in funding for vegetation and watershed management, a 68% reduction for recreation and administrative facilities, a 18% reduction in wildlife and fisheries habitat management, and a 46% reduction for the maintenance and construction of roads (US Department of Agriculture, 2015). Furthermore, fire suppression costs as a portion of the Forest Service's budget are projected to continue rising to 67% by 2025. Based on this projection, the funding allocated to non-fire programs would drop by approximately $700 million between 2015 to 2025 (US Department of Agriculture, 2015).

Policy makers must allocate scarce resources between competing alternatives. Economic efficiency should be a major criterion for determining priorities. Therefore, there is a growing need for policy makers to evaluate the full cost of wildfires in order to create effective fire management strategies and policies. To evaluate the full cost of wildfires, policy analysts seek both market (e.g., protection and suppression cost) and non-market cost estimates (e.g., health impacts from wildfire smoke) (L. A. Richardson, Champ, & Loomis, 2012). Market costs are generally easy to measure while non-market costs are not.

1.2 Motivation, research method and conclusions

One of the non-market costs of wildfires is their impact on property value where the property itself is unscathed. These properties may also experience reductions in sale prices. With the rapid expansion of WUI, more houses are exposed to elevated wildfire risks, and therefore this non-market cost is expected to increase. Thus, estimating the effect of wildfire on property values is of increasingly critical importance.

Several studies have quantified the effects of wildfire on property values through the hedonic pricing model, which is the most commonly used method to derive the relationship between property values and the environmental attributes. Previous hedonic papers examine the association between wildfire and property values from two perspectives: the effect of wildfire occurrence and the effect of wildfire risk. However, these papers have several limitations. First, these studies examined the effect of occurrence and risk independently, and have overlooked any potentially confounding influence. Secondly, these studies found mixed effects. In some cases, wildfire occurrence is negatively associated with property values, in others wildfire effects vary by space and time. Wildfire risk effects are complicated by the fact that factors contributing to high risk are also associated with high amenity values, such as a view of a forest. These two have opposite effects on property values: fire risk lowers value while attractive features raise it. Thus the overall predicted effect of wildfire risk is ambiguous. Third, mixed and/or inconsistent results found across studies are further complicated by model uncertainty, including a variety of data employed by the analysts as well as varied econometric modeling decisions.

Model uncertainty is well acknowledged in quantitative modelling. There is little theoretical guidance with respect to the best model specification, and thus the analyst generally conducts a large number of models. For example, the analyst can employ either linear or nonlinear functional form. However only a small proportion is published because of limited journal article spaces. In such case, one common practice is to selectively report model results based on a specific statistical measure (e.g. R-squared value) or models that yield significant parameter estimates (also referred to as publication bias). However, parameter estimates can vary consideratеly across different model specifications. That is, model uncertainty may result in large variation in estimates. Since only a restricted portion of estimated models is published, this creates asymmetric information between the analyst and the readers, and therefore, the readers have no information about changes in estimates. This dissertation contributes to the literature by utilizing multiple data and econometric specifications to investigate wildfire effects on property value, and then summarizes how data and model specification affect variation in wildfire effects.

This analysis applies spatial econometrics modeling strategies in a hedonic pricing model (HPM) framework to examine the joint effect of both past wildfire events and current risk on property values in Santa Fe County, New Mexico. We select Santa Fe County as study area for two reasons. First, this area has experienced severe wildfire situations, which have posed a threat to Santa Fe watershed, the major water source for Santa Fe city. Secondly, a fair amount of residential properties were located in the WUI, facing relatively high fire risk.

For past wildfire events, I use wildfire perimeter data for fires that burned at least 10 acres in two national forests: Santa Fe National Forest and Cibola National Forest. A portion of Santa Fe National Forest is located in the County; Cibola National Forest is adjacent to the southwestern corner of the County. Thus fires in these two forests may have impacts on housing prices in the County. I collect three wildfire risk data, which were assessed at different geographical scales (county, community and house level, respectively). The objective of this analysis is twofold. First, I investigate wildfire effects on property values. To accomplish this, I systematically examine wildfire effects using a variety of modeling approaches, including varying or alternative measures for property values, wildfire event/occurrence and risk, and econometric modeling techniques. Secondly, using results of hedonic models as primary estimates, I then investigate how the effect of wildfire varies with data availability and econometric modeling decisions through internal meta-analysis.

The systematic investigation can be grouped and classified as measures for property values, wildfire occurrence and risk (which capture data availability issues), or econometric modeling techniques (which capture subjective modeling decisions of the analyst). Specifically, I employ two data measurements for property values: assessed property value and estimated sale price. Two measures of past wildfire event/occurrence were used: the nearest fire and the aggregate fire, each with two time frames (7-year and 15-year time window). The nearest fire measure focuses on the nearest fire burned for each property while the aggregate fire measure examines the effects of fires burned within a certain radius. For the nearest fire measure, three variables are considered: the distance from the house to the nearest fire, time since the nearest fire burned, and the size of that fire. For the aggregate fire measure, two variables are included: the number of fires burned within a certain radius and the average size of these fires. The variables of interest are distance from nearest fire and the number of fires burned, respectively. In this analysis, four radiuses are considered: fires burned within 10km, 15km, 20km and 25km of the property. In addition, two time frames are included. 7-year time window considers fires burned in the 7 years prior to the sale while 15-year time window considers fires burned in the 15 years prior to the sale; these two time windows are expected to capture the short- and long-term effect of wildfire on property values. Three categories of wildfire risk (composite risk, WUI risk, and house risk) were collected; these risks were assessed at different geographical scales (county, community and house level). It’s possible that homeowners’ perception of wildfire risk varies across geographic area. Thus I run further models with three geographic areas: Santa Fe County, the Non-WUI area, and the WUI area. I also consider a variety of model specifications, including four spatial dependency approaches (independent/OLS, spatial lag, spatial error, general spatial model), with three weighted matrix structures (the four nearest neighbors, the eight nearest neighbors and the distance inverse weight matrix). Finally, I employ two commonly used hedonic functional forms: semi-log and double-log. Overall, this analysis employs two data sets for property values, 10 measurements of wildfire event/occurrence, three risk measures (with three geographical areas for composite risk), four spatial dependency models with three spatial weight matrices, and two hedonic functional forms to produce 2,000 regression results for hedonic model.

I expect past wildfire events/occurrences have a negative effect on property values. There is no a priori expectation about the relationship between wildfire risk and property values, given that wildfire risk and amenity values are confounded in the risk assessment and they have opposite effects on property values. Amenities tend to increase property value while risks tend to decrease property value. I hypothesize that risk effects differ across geographic areas. In the Non-WUI, where fire risk is relatively low, people tend to place more value on amenities, thus the positive effects of amenities dominate and fire risk is positively associated with property values. In the WUI, the negative effects of wildfire risk offset, or even exceed the positive effects of amenities, resulting in a non-significant or negative relationship.

Consistent with the hypothesis, past wildfire events/occurrence have a negative effect on property value. Results show that an additional kilometer away from nearest fire would increase property value by $3,461, implying an increase in assessed value of 1.1%. Property value decreases by $14,375 for one additional burn near the houses, implying a decrease in assessed value of 4.6%.

The effect of wildfire risk is mixed. First, wildfire risk effects depend on risk measurement and risk level. For composite risk and WUI risk, the effects of risk change when risk achieves a certain level of risk. Property values increase with the increase in the risk at low risk levels. If risk reaches a certain threshold, the relationship becomes negative or insignificant. For house level risk, it has a negative effect on property value. Secondly, the effect of composite risk depends on geographic area, as expected. In the Non-WUI area, the positive effects of amenity dominate, and thus wildfire risk increases property value. However this relationship becomes negative or insignificant in the WUI area.

The estimates indicate that houses located in zones with higher risk rating have higher values, except for houses located in the very high WUI risk zone. The increase in property value ranges from $7,040 to $22,611, indicating 2.2% and 7.2% of assessed value, respectively. However, if risk is measured at individual house level, 1-point increase in house risk score would decrease property value by $565, which represents a 0.2% drop in assessed value.

Meta-analysis results also show that models that use assessed value data not only give higher R^2 but also find more significant estimates and larger MIP estimates than models that use estimated sales prices data. However, the assessed value models do not necessarily yield estimates with smaller standard errors. Second, ignoring spatial autocorrelation would lead to overestimate of MIP or it has no significant effect on MIP estimates. Third, the measurement of wildfire risk influences the effects of fire event/occurrence. This result reveals the importance of joint estimation of wildfire events and risks, and ignoring wildfire risks in hedonic models may yield inaccurate estimates.

1.3 Outline of the dissertation

The reminder of the dissertation is organized as follows. Chapter 2 gives an overview of the literature on the economic impact of wildfire effects on property values, and summarizes the contribution of this research. Chapter 3 describes the study area, Santa Fe County, New Mexico and reasons for selecting this area. Chapter 4 introduces the hedonic theory, functional form and spatial autoregressive models. Chapter 5 describes the data and our hypothesis. Chapter 6 presents test statistics for spatial autocorrelation and results of selected hedonic models. Chapter 7 first summarizes the descriptive statistics for results of hedonic model, and then investigate variation in the results via internal meta-analysis. Chapter 8 presents our conclusions, reviews the limitations of the research and discusses its policy implications. What follows is a more detailed overview of each chapter.

• Chapter 2 critically reviews the literature on the economic impact of wildfire on property values from two perspectives: the effect of wildfire event/occurrence and the effect of wildfire risk. Mixed and/or inconsistent results are found across studies. I then explore possible explanations for these mixed results, including regional variations in historical fire characteristics, varying measurements for data and the analysts' subjective decisions about constructing their econometric models. This paper contributes to the literature in that it utilizes a variety of data and econometric modeling techniques to investigate the effect of wildfire risk and occurrence on property values and examines what factors influence the variation in wildfire effects.

• Chapter 3 describes the environment of the study area, Santa Fe County, New Mexico. These characteristics include location, geography, topography, climate, vegetation and demographics. The reasons for selecting this study area are twofold: severe wildfire situation (pervasive wildfires, wildfire threat to watershed) and rapid home development in the WUI.

• Chapter 4 first introduces hedonic price theory and functional forms commonly used in hedonic analysis. I then take into account spatial econometric techniques, including spatial models, spatial weight matrix, tests for spatial dependence and estimation methods.

• Chapter 5 explains the data used in hedonic model and defines our hypothesis. Specifically, I employ two measures for property values (assessed value and estimated sales price), two measurements of past wildfire occurrence (the nearest fire and the aggregate fire), and three risk measures assessed at county, community and house level, respectively. I hypothesize that property values decrease with past wildfire events/occurrences; the effect of fire risk differs across geographic areas. I then present an overview of the data and econometric modeling techniques in this analysis, which produces 2,000 estimated hedonic models for the estimating equations.

• Chapter 6 explores the spatial correlation in the data and the preferred model specification by utilizing test statistics, Moran's I and LM test, and then selectively reports results of hedonic models. Results demonstrate that a spatial correlation is found in the vast majority of the models. Further, the preferred model specification vary by the choice of data (measurement for the dependent variable, past wildfire event/occurrence and risk) and econometric modeling decisions (functional form, spatial model and weight matrix).

• Chapter 7 summarizes results of 2,000 hedonic models via meta-analysis and investigates the variation in wildfire effects. Using the results from these 2,000 hedonic models as primary estimates, first results show the expected negative effect of wildfire event/occurrence. The effect of wildfire risk varies widely, depending on the measurement of fire risk, level of risk and the geographic area. Two meta-regressions find that data and econometric specification have significant effects on MIP estimates.

• Chapter 8 summarizes the results, discusses the limitations of the research, prospects for future research and the policy implications.

Chapter 2 Review of wildfire impacts on housing prices and our contribution

This chapter provides a critical literature review on the economic impacts of wildfire effects on property values. Previous studies have investigated the effect of wildfires from two perspectives: the effect of wildfire events/occurrences and the effect of wildfire risk. One caveat of previous research is that the effect of wildfire event/occurrence and risk were examined independently, overlooking the potential confounding influence. Overall, previous studies indicated mixed and/or inconsistent results, which might be attributable to varying measures for housing prices, past wildfire event/occurrence and risk, and the analysts' decisions about model specification.

2.1 The economic impact of wildfire on housing prices

2.1.1 Wildfire event/occurrence effects on property values

The first study to quantify the economic effect of a fire event on property value focuses on the Cerro Grande Fire. However this study didn't utilize a hedonic model. It only compared housing prices before and after the fire. The Cerro Grande Fire, which started as a prescribed burn in May 2000, burned 48,000 acres, destroyed 235 homes and damaged 39 others near Los Alamos, New Mexico. In 2001, Price Waterhouse Coopers conducted a study to examine how the real estate market responded to this fire event immediately following the fire. Specifically, the primary interest was "whether the fire caused a decline in property values and, if so, which types of properties and which communities or neighborhoods were most affected" (Pricewaterhouse Coopers, 2001, p. 3). Using housing transactions between January 1996 and January 2001, the study compared price trends in Los Alamos before and after the fire, as well as price trends across Los Alamos and similar communities. The study focused on single family houses not physically damaged in the fire. Results indicated that, after the fire, their sale prices dropped from 3% to 11%. It should be noted that this study only examined the effect of fire for a short post-fire period (seven months after the fire).

Later studies utilized hedonic model to examine the effect of past occurrence of wildfires, which are summarized in Table 2.1. I further classify the literature into two categories based on number of fires examined in the study. The first branch of the literature focused on a single fire event or multiple large, severe fires while the second branch focused on a large number of wildfires.

2.1.1.1 Hedonic studies focusing on a single fire or multiple large, severe fires

J. Loomis (2004) assessed the effect of the Buffalo Creek fire, which burned about 5,000 hectares in 1996, on house prices in the nearby unburned town (two miles away from the fire). The author included a pre-post fire dummy variable to indicate whether the property was sold prior or following the fire and compared house prices sold three years before the fire and five years after the fire. Results indicate the negative effect of fire on house prices, with selling prices dropping about 15% and 16% in the linear and semi-log model, respectively. However, given the short period studied, it is difficult to determine the negative effect of the fire and the reduced level of amenities (e.g., burned forest in the view) separately since the natural vegetation affected by the fire needed several years to regenerate.

Huggett Jr, Murphy, and Holmes (2008) undertook an hedonic analysis to investigate the effect of three fires on house prices. These three fires, occurred during the summer of 1994 in Washington, was treated as a large fire event in the study. The analysis utilized a semi-log functional form but did not control for spatial correlation. The variables of interest are distance from the house to the fire and a set of interactions between the distance and time of sale (e.g., 6 months, 6-12 months after the fire). The study found that, prior to the fires, houses near a potential fire area tend to have a higher price due to the possible amenity values associated with wilderness, and the fire then causes a decline in the housing prices. Specifically, a one kilometer reduction in the distance from a house to the burned area increases house prices by $676 prior to the fires while it decreases prices by $48 following the fires. This price drop is only observed in the immediate aftermath of the fire, which lasts for six to twelve months.

J. Mueller, Loomis, and González-Cabán (2009) studied a region in Los Angeles County affected by repeated fires in the 1990s, then compared the short- and long-term effects of these fires. The analysis employed several functional forms (e.g., semi-log and double-log) in the standard hedonic model. The time interval between the first and second fires ranged from two to six years. Only houses within 1.75 miles of each fire were included in the analysis. Houses might have been affected by a varying number of fires (none, one, two, or three) depending on location and time of home sale. The main variables of interest that had the largest effects were whether a house experienced at least one fire, whether the house experienced at least two fires, days since the first fire, and days since second fire. They find that both fires had a negative effect on house prices; the second fire caused house prices to drop more. Opposite signs were detected for days since the first fire and days since the second fire. Although both fires would cause an initial drop in the house price, it continued to decrease after the first fire while it tends to increase after the second fire. According to their results, it generally takes five to seven years for house prices to recover following the second fire.

Using the same data, J. M. Mueller and Loomis (2014) employed quantile regression to estimate marginal implicit prices across different quantiles of house price. They found a large difference in the estimated implicit price for the first and second fire between the 0.25 quantile model and the 0.75 quantile models, which can be as high as $72,000 for the first fire and $99,000 for the second fire.

J. M. Mueller and Loomis (2008) further explicitly identified and controlled for the spatial correlation and compared marginal implicit price across the OLS and spatial models. Spatial correlation was tested using Moran's I and LM statistics, which indicate that the spatial error model is the appropriate alternative. Three weight structures were then employed to define the weight matrix: the four nearest neighbors, the eight nearest neighbors and the inverse-distance weight matrix that ensures each property has at least one neighbor. Overall, fire events would lower house prices and the OLS always over-estimates the drop. The largest difference between the OLS and spatial correlated models is 24%. Thus they infer that OLS yields reasonable implicit price estimates even in the presence of spatial correlation given the relatively small difference in the implicit price across the OLS and spatial models. In a subsequent study, J. M. Mueller and Loomis (2010) details the use of the Bayesian estimation approach for choosing the appropriate spatial model and weight matrix. They compared the performance of three spatial models (spatial lag, spatial error and the spatial Durbin models), each with three weight matrix structures (the four, six and eight nearest neighbors and the inverse-distance weight matrix), using posterior probability. The Bayesian estimation method found support for the spatial error model with the inverse-distance weight matrix. They found a relatively small variation in the estimated implicit price (5%) between 12 models.

2.1.1.2 Hedonic studies focusing on a large number of fires

Stetler, Venn, and Calkin (2010) studied the effects of 256 wildfires on house prices in northwest Montana. They focused on fires larger than four hectares that burned between 1996 and 2007. The primary variables of interest are the distance from the nearest fire to the house, time since the fire, size of the nearest fire and whether there is a view of the fire. For each house included in the study, the authors selected the nearest fire burned in the seven years and found that wildfire had had a dramatic negative effect on home prices, with prices dropping farther as the distance between the house and the burned area diminished. However, housing prices decrease with time since fire. That is, housing price would decrease with the increase in the time lag between fire and sale. One possible explanation is the short time window of fire history relative to the recovery of housing market; the paper only included fires burned in the last seven years. The authors also factored in the view of the burn from the home. As expected, house prices dropped to a greater extent if the burned area could be seen from the home.

Instead of focusing on the nearest fire, Xu and van Kooten (2013) examined the effect of occurrence and average size of fires within a varying radius of each property in Kelowna, BC, Canada. The analysis utilized semi-log functional form and two measures for property value: sale price and unit price (price per square meter). Spatial correlation is detected in the sale price model but not in the unit price model. Specifically, they analyzed the effect of fires burned in the last 10 years prior to the sale of the house. The authors compared the fire effect according to radius constraints: 0.5km, 1km, 2km, 5km, and no limit, with an interest in two variables: the number of fires burned within the radius and their average size. Surprisingly, the occurrence of fire is found to be statistically insignificant. Counterintuitively, the larger the average size of a fire, the higher the house price. The authors argued that large fires lower the potential for future fires, thereby lowering a homebuyer's perceived risk, which eventually increases property value.

Another study by Hansen and Naughton (2013) studied the effects of wildfires and bark beetles on assessed property values in the WUI of south-central Alaska. Since Alaska is a non-disclosure state, sale prices are not publicly available. Therefore, the assessed property value is used instead of house sale price. The authors categorized fires by their size (less than 3.3 hectares is considered small, while anything larger is classified as a large fire), distance from the fire to the house (less than 0.1 km, 0.1 to 0.5 km, 0.5 to 1km, and greater than 1km), and number of years since the fire occurred (1 to 5 years or 6 to 20 years). Generally, wildfires increase property value with the exception of small fires that are nearby. The positive relationship can be explained, for example, by the fact that nearby large fires may result in a better view of the ocean or mountains and reduce the perceived risk of future fires. Nearby small fires, on the other hand, decrease home value since their presence is a reminder of wildfire risk. Large wildfire effects on assessed value increase over time, while small wildfire effects diminish with time.

2.1.2 Wildfire risk effects on property values

Two studies have explicitly examined the effect of wildfire risk and one study investigated the impact of disclosure of fire-hazard zone. All three studies are reported in Table 2.2.

Donovan, Champ, and Butry (2007) addressed the effect of wildfire risk on house prices. This risk rating was calculated by the Colorado Springs Fire Department, posted on its website and publicly available in July 2002. Risk rating is computed based on a variety of underlying factors, including proximity to dangerous topography, the type of roof and siding material, vegetation and terrain characteristics, and then is rated in a categorical manner (as low, moderate, high, very high or extreme). They collected sale prices for the three years before the disclosure of risk rating and three years after. The main variables of interest are the underlying factors used to compute the rating and the categorical risk ratings in both pre- and post-web site models. The analysis explicitly takes the spatial correlation into account and it utilized general spatial model. The study found the categorical risk rating had positive effects on the prices of homes sold prior to publication on the website but insignificant effects for houses sold post-website publication. On average, price is found to be $40,000 lower for houses sold after the publication of these factors on the website. Since wildfire risk and amenity values are compounded in the risk rating and they have opposite effects on house prices, the authors argued that the positive amenity effects outweighed the negative effects of wildfire prior to publication of the ratings on the website. However, the amenity effects were offset by the wildfire risk after website publication. Further investigation indicated that a structure's materials, particularly roof and siding, have a dramatic effect on the association between risk ratings on home prices in the pre- and post-web site model. Using the same risk assessment, Rossi (2014) examined the effect of wildfire risk rating on housing prices. Surprisingly, results showed that wildfire risk has no significant effect on house prices. One possible explanation is that the positive effects of amenities on price cancel out the negative effect of risk.

The Natural Hazard Disclosure law (AB 1195) was passed in 1998 in California, which requires the seller to disclose when a property lies within a hazard zone that caused by fire, flood, or seismic conditions. Troy and Romm (2007) examined the effect of fire risk disclosure on house prices using a hedonic price model. It should be noted, however, that information on fire risk levels are not available, thus the analysis is focused on the impact of disclosure of fire-hazard zone rather than the specific effect of risk level. Further, the author also factored in wildfire event/occurrence by including a dummy variable to indicate property's proximity to a burned area, which allows one to examine the combination effect of wildfire event/occurrence and risk disclosure. Mixed results were found. If one only considers the effect of risk disclosure, implementation of the law doesn't have a significant effect on prices for houses located in a fire hazard zone. However, if one also takes into account wildfire event/occurrence, the passage of the law increases prices in the fire hazard zone, except for properties located near a recent major fire. Specifically, for houses located in a fire hazard zone and sold after passage of the law, price is found to be 5.1% lower when the property is near a burned area. The negative effect of wildfire event/occurrence is in line with previous results in the hedonic studies whereas the effects of fire risk zone disclosure seem to be contrary to the results in Donovan et al.,

2.2 Summary

Summarizing the reviewed wildfire hedonic studies, first one can see that previous studies have examined the effect of past wildfire event/occurrence and wildfire risk independently. Secondly, one finds that the effects of wildfire on housing value vary across different studies. Some studies find that wildfires decrease housing value, while in others the effect of wildfires is mixed. Overall, one can see that wildfire effects vary spatially and also temporally. It is difficult to compare the estimates across the studies as measures for housing prices, past occurrence and risk, as well as econometric modeling techniques vary across those studies.

With respect to data for housing prices, previous wildfire hedonic studies exploit the actual sale prices as the dependent variable. Xu and van Kooten (2013) utilized both the sale price and the unit price, which is calculated as the price per square meter. Hansen and Naughton (2013) used assessed value data given that the study area is within a non-disclosure state where sale prices are not publicly available.

Secondly, various measures were constructed to capture wildfire event/occurrence in earlier hedonic studies. Some used dummy variables to model wildfire event/occurrence, including whether the property experienced large fires within a certain radius (J. Loomis, 2004; Hansen & Naughton, 2013), while others utilized a combination of dummy and continuous variables, such as the distance from the fire (Huggett Jr et al., 2008; J. M. Mueller & Loomis, 2008; Stetler et al., 2010). In addition, the reviewed wildfire hedonic studies cover a variety of locations. Historical wildfire characteristics (e.g., fire size, severity and frequency) associated with these sites may vary substantially by location, although the studies generally choose areas vulnerable to wildfires or areas with high fire risks. For example, the frequency of fires ranges from infrequent, to moderate to infrequent and moderate to frequent (Hansen, Mueller, & Naughton, 2014). Further, some studies covered solely the WUI area (e.g., Hansen & Naughton, 2013) while others examined the Non-WUI as well (e.g., Stetler el al., 2010). Thus, comparing wildfire effects across studies is constrained by wide variation in historical fire characteristics as well as varied measurements for past occurrence.

Third, varying measurements for wildfire risk were utilized. Two studies, Donovan et al. (2007) and Rossi (2014), utilized a risk rating assessed at house level; Troy and Romm (2007) examine the effect of risk disclosure. Although fuel, topography and weather are three risk factors typically thought to affect fire risk, assessments conducted at different geographical scales may vary with regard to underlying risk factors, and therefore result in different effects of risk on property values. For example, an assessment conducted at the community level may put more weight on the average characteristics of that community, such as the availability of fire hydrants or water.

Finally, researchers utilized a variety of econometric modeling techniques in previous wildfire hedonic studies. For example, several functional forms have been employed: linear, semi-log (also called log-linear) and double-log (also called log-log). Moreover, there is no consensus regarding the importance of spatial autocorrelation. Most early works only use the standard hedonic model or OLS model while later studies explicitly take into account spatial autocorrelation. Also, there does not seem to be any consensus about the preferred model specification. For example, J. M. Mueller and Loomis (2008) exploited the spatial error model; Hansen and Naughton (2013) and Donovan et al. (2007) utilized the general spatial model, a combination of the spatial lag and spatial error model.

2.3 Our contribution

This study focuses on Santa Fe County, New Mexico. Focusing on a single study area eliminates the potential variation in the wildfire effects caused by varying historical fire characteristics. To examine the sensitivity of wildfire effect to data feature, I first utilized two data for housing prices: estimated sale prices (derived from the mortgage amount) and assessed value. Thus the data allow us to estimate two hedonic models, one with the assessed value, the other with the estimated sales price. Secondly, I adopt two measures of wildfire event/occurrence: one considers the nearest fire for each property and the other considers fires burned within a certain radius. I also utilize three measurements for wildfire risk, assessed at county, community and house level, respectively. These three risk assessments are somewhat similar in that they all consider fuel, topography and weather as underlying risk factors. However, they have significant differences, such as different weight put on each factor, which may affect the impact of risk on housing prices.

With respect to econometric modeling techniques, I first exploit two widely used hedonic functional forms: semi-log and double-log. Secondly, I explicitly address spatial dependence in hedonic model, and compare the results across OLS models and three spatial autoregressive models: spatial lag, spatial error and general spatial model, with three spatial weight matrix structures (the four nearest neighbor, the eight nearest neighbor and the distance inverse weight matrix).

Wildfire effects can vary considerately across models that utilized different data or models that employ different specifications. This analysis contributes to the literature by utilizing multiple data and econometric specifications to investigate wildfire effects on property value, and then summarizes how data and model specification affect variation in wildfire effects via meta-analysis. This approach enables us to examine the variation in wildfire effects across alternative models while also improving the robustness and reliability of our results in ways that are useful for informing policy recommendations.

Table 2.1: Summary of the effect of wildfire event/occurrence in hedonic model

Study[a]	Area	Wildfire event/occurrence	Spatial model	Functional form	Result
(1) Studies focusing on a single fire or multiple large, severe fires					
Loomis (2004)	CO, US	Sold post fire=1, 0 otherwise	No	Linear and semi-log	Negative; 15% and 16% dec. in the linear and semi-log model, respectively
Hugget et al. (2008)	WA, US	Distance to the closest fire; interaction of distance and sale time (during the fire, 6, 6-12, 12-18 and 18-24 month after the fire)	No	Semi-log	Negative; $676 dec. per km farther away from the fire before the fire; $48 inc. per km after the fire
Muller and Loomis (2008)	CA, US	Days since most recent fire; experienced at least one fire=1, 0 otherwise; experienced at least two fires=1, 0 otherwise	Error	Semi-log	Negative; $29,802 to $32,547 dec. for the first fire; $16,161 to 21,274 dec. for the second fire; diff. ranges from 5% to 24% between the OLS and spatial models
Muller et al. (2009)	CA, US	Days since the first fire; days since the second fire; experienced at least one fire=1, 0 otherwise; experienced at least two fires=1, 0 otherwise	No	Semi-log, double-log and quadratic	Negative; $14,744 (10%) dec. for the first fire; $34,453 (23%) dec. for the second fire
Muller and Loomis (2010)	CA, US	Days since most recent fire; experienced at least one fire=1, 0 otherwise; experienced at least two fires=1, 0 otherwise	Error	Semi-log	Negative; larger dec. in price in the OLS, about $11,986 (5%)
Muller and Loomis (2014)	CA, US	Days since most recent fire; experienced at least one fire=1, 0 otherwise; experienced at least two fires=1, 0 otherwise	No	Semi-log	Negative; 94,728 to $167,104 dec. for the first fire; $63,790 to $163,080 for the second fire
(2) Studies focusing on a large number of fires					
Stetler et al. (2010)	MT, US	House located within 0-5, 5-10, 10-15, 15-20 km from the nearest fire; quarter since fire; View of fire=1, 0 otherwise; size of the fire (>405 ha) =1, 0 otherwise; located in WUI=1, 0 otherwise	No	Double-log	Negative; $33,232 (13.7%) lower within 5km; $18,924 (7.6%) lower between 5k and 10k; $301/quarter since fire dec. $6610 lower with a view of burned area; $7,076 lower in the WUI
Hansen and Naughton (2013)	AK, US	Large fire (>3.3 ha) within 0.1, 0.1-0.5, 0.5-1 km of a house; small fire (<3.3 ha) within 0.1km, 0.1-0.5 km, 0.5-1km of a house; each then interacted with two time frames (<5 years, 6-20 years)	General	Double-log	Conflicting; 18.6% inc. for large fire within 0.1km; 2.4% inc. for small fire within 0.1-0.5k; 5.5% dec. for small fire within 0.1km. Large fire effect is magnified with time while small fire effect diminish with time.
Xu and Kooten (2013)	Kelowna, BC	The number and average size of fires within 0.5, 1, 2 and 5km of a house as well as no radius limit	Lag	Semi-log	Conflicting; $3.93 dec. in unit price for one extra fire within 5km; $-3,663 to $21,604 changes in sale price for one-hectare increment in the average size of fire, $4.45 to 42.41 inc. in unit price for one-hectare increment in the average size of fire.

[a] Studies utilized house sales prices as the dependent variable in the hedonic model except for Hansen and Naughton, which used assessed property value. Xu and Kooten employed both house price and unit price (price per square meter) as the dependent variable.

Table 2.2: Summary of the effect of wildfire risk in hedonic model

Study[a]	**Area**	**Wildfire risk**	**Spatial model**	**Functional form**	**Result**
Troy and Romm (2007)	CA, US	Located in fire hazard zone=1, 0 otherwise; interaction of located in hazard zone and sold after risk disclosure; interaction of located in hazard zone, sold after risk disclosure and near a recent and major fire	No	Semi-log	Conflicting; risk disclosure increase prices in fire zone except for locations near a major fire
Donavan et al. (2007)	CO, US	Risk rating dummies (moderate, high, very high and extreme); distance to dangerous topography (<30 feet, 30-100 feet); veg. density within 30 feet of the house (dense and moderately dense), average slope within 150% of house, wood roof=1, 0 otherwise; wood siding=1, 0 otherwise	General	Double-log	Negative; $40,000 dec. in price post-web site; wood roof inc. price pre-web but dec. price post-web; wood siding insignificant pre-web but dec. post-web
Rossi (2014)	CO, US	Risk rating dummies (moderate, high, very high and extreme)	No	Semi-log	No effect

[a] All studies utilized house sales prices as the dependent variable.

Chapter 3 The Study Area: Santa Fe County, New Mexico

In this chapter, I begin by introducing the environment of Santa Fe County, including location, geography, topography, climate, vegetation and demographics. Then, I illustrate two reasons for selecting Santa Fe as the study area. First, Santa Fe County has experienced severe wildfire situations, especially in the northern forest region. Wildfires pose a serious threat to the Santa Fe watershed, which, in turn, can affect infrastructure, property, human life and ecological environment significantly. Second, a fair amount of the county's residential properties is located in the WUI, facing relatively high wildfire risks.

3.1 Environment of Santa Fe County

The study area for this research was Santa Fe County (Figure 3.1), which is located in the north-central portion of New Mexico and surrounded by seven counties (Los Alamos, Sandoval, Bernalillo, Torrance, San Miguel, Mora and Rio Arriba). Santa Fe County is about 70 miles long and 30 miles wide, covering an area of 1909 square miles. Of that, about 60% of the land is privately owned. US Forest Service owns approximately 20% of public land, followed by native tribes (8%), the state of New Mexico (6%) and the Bureau of Land Management (6%). The county includes one major city, Santa Fe, and one town, Edgewood. The city of Santa Fe is the capital of New Mexico. Two interstate routes run through Santa Fe County: north-south interstate 25 and east-west interstate 40. US Route 285/84, and New Mexico Routes 14 and 41 run north-south through the study area. Overall, the majority of the study area is relatively flat with desert plains and small hills except for the highly mountainous regions of northeastern

Santa Fe. The state has an arid to semi-arid continental climate, with abundant sunshine and low precipitation rates (Western Regional Climate Center, 2008).

According to the NatureServe United States Ecological Systems categories, vegetation in the study area consists of a mosaic of grassland communities (48%), forestland communities (46%), riparian woodlands and wetlands (2%), and other types (4%), such as agricultural and developed areas (NatureServe, 2007). The largest share of forested communities is the Southern Rocky Mountain Pinon-Juniper Woodland, constituting of approximately 60% of the county's total forest land. This forested community is characterized by a mixed-severity fire regime, where severity can vary from non-lethal surface fires to lethal stand replacement fires (Keeley, 2009). This regime is responsible for one of the most widespread disturbances influencing western forests. Western Great Plains Shortgrass Prairie dominates the grassland community and accounts for approximately 46% of the total grass land. This grassland community has a low fire risk and low frequency of fires due to low fuel load; the fuel load is reduced in the western US by the arid to semi-arid continental climate (NatureServe, 2007).

According to the 2010 United States Census, Santa Fe County has a population of 144,170 (US Census Bureau, 2010). Santa Fe city is the most populated city, with 81,153 residents. Throughout the county, there are about 61,313 households, with 2.34 persons per household. Out-of-state owners own about 11.2 percent of residential homes within Santa Fe County; this ratio increases to 16.2 percent in Santa Fe city (Last, 2015).

About 51% of the population is female. 15% of residents are age 65 and over. 88% of residents age 25 and over have completed a high school degree or higher. 76% of residents identify as Caucasian compared to the US average of 72%. According to the

2010-2014 estimates, the median household income and *per capita* income is $52,958 and $32,454, respectively. The median household income is slightly lower than the national median house income ($53,482) while the *per capita* income is somewhat higher than the national level ($28,555). Most economic activity in the County centers on tourism and recreation.

3.2 The wildfire problem

3.2.1 Past occurrence

I focus on the wildfire situation in two national forests: Santa Fe National Forest and Cibola National Forest (Figure 3.2). A portion of the Santa Fe National Forest is located within Santa Fe County. Although located outside the boundaries of Santa Fe County, Cibola National Forest is adjacent to the southwestern corner and has wildfires that may have an impact on housing prices, and is thus included in the study.

Santa Fe National Forest encompasses approximately 2,435 square miles and is made up of five separate ranger districts: the Coyote, Cuba, Española, Jemez and Pecos/Las Vegas Ranger Districts. A portion of the Pecos/Las Vegas Ranger District is located in the north eastern part of the county. Two regions within the Española Ranger District are in Santa Fe County. One is located west of Santa Fe city and the other is located north of the city. Cibola National Forest covers an area of approximately 2,553 square miles in New Mexico. This forest is divided into four ranger districts: Sandia, Mountainair, Magdalena and Mount Taylor. Of the four districts, Sandia Ranger District is adjacent to the county’s southwestern boundary. The shortest straight-line distance between the district and county boundary is about two miles.

According to wildfire event/occurrence data over the period 1970 to 2013 (US Department of Agriculture, 2013), there were 9,609 fires reported in both forests during this period. The number of fires has declined in the last two decades, from an annual average of 278 fires during 1993 to 2006 to 143 fires in 2007 to 2013. July has the highest number of fires, followed by June, August and May. Figures 3.3 and 3.4 illustrate activities of fires that burned at least 10 acres. 512 fires occurred in both forests, with an average of 11.6 fires burned per year. The average size burned is 12,571 acres per year with the total average area of 553,134 acres burned. It should be noted that, although the number of fires is relatively low in the last ten years, the total area burned is quite large and reached its highest level in 2011, at about 170,000 acres. Furthermore, of the 512 fires burned, the vast majority of the fire (67%) are caused by lightning. The second major cause of fire is human activity, such as campfires, smoking, etc.

3.2.2 The threat of wildfire to watershed

Large and severe wildfires can cause severe damage to the Santa Fe Watershed, the major water source for Santa Fe city. The watershed is located on the west side of the Sangre de Cristo Mountains, northeast of Santa Fe city. It covers an area of 17,520 acres, with the vast majority owned by the Santa Fe National Forest (88%). As the primary drainage in the watershed, the Santa Fe River in the watershed collects rainfall and snowmelt from the Sangre de Cristo Mountains and provides water to two reservoirs: the McClure and Nichols, which supply approximately 40% of Santa Fe city water (Steelman & Kunkel, 2003).

Over the past century, institutionalized fire suppression and livestock grazing in the watershed resulted in increased fuel accumulation as well as low levels of understory vegetation. The long-run effect is an unnaturally dense forest in the watershed, which places the area at high risk for large fires, insect outbreaks and reduced biodiversity (Steelman & Kunkel, 2003). Additionally, the watershed is expected to experience fire every 15 years according to an estimation by Balmat, Baisan, and Swetnam (2005). However, this area has not seen widespread fire for approximately 100 years, which also leads to a high fuel load, and thus high risk of severe fire. Furthermore, according to Santa Fe CWPP WUI risk assessment in 2007, the watershed is located in the WUI, which is at very high risk from wildfire. According to the core team of the Santa Fe Watershed Investment Program, $5.1 million is needed to treat and maintain forests to protect the watershed from 2010 through 2019, an annual average of $258,000. Since 2013, this program is mainly paid for by the Santa Fe water utility's rate payers via a higher monthly water bill. The average ratepayer needs to pay an additional $0.65 a month or $7.8 a year[1]. The amount totaled $220,000 a year.

High severity fire poses a serious threat to the Santa Fe city water supply. Wildfires can influence the hydrologic cycle of the watershed in many ways, the two most important ones being the reduction in vegetation interception and soil infiltration. First, wildfires would consume the surface vegetation and litter layer, resulting in decreased vegetation cover and interception loss. Second, change of soil properties can also be attributed to wildfires, perhaps the foremost change being the development of hydrophobic soils (Ice, Neary, & Adams, 2004; Larsen et al., 2009). The consequences of

[1] Based on a contingent valuation survey, 82% of rate payers are willing to pay 65 cents a month for the fund.

the reduction in ground cover and soil infiltration is a significant increase in surface runoff and erosion (Parlak, 2015).

Surface runoff and erosion have dramatic consequences for water quality and quantity, which, in turn, can affect infrastructure, property, human life and ecological environment significantly. Runoff and erosion generally lead to increased sediment, debris, chemicals or other pollutants transported to streams, rivers and reservoirs. This may cause water quality degradation, actual damage to dams, reservoirs and water-treatment plants, as well as a reduction in water storage capacity and thus threaten water supply. This may also damage the flood control system for reservoirs and lead to heavy flooding in the downstream area. Beyond this damage, excessive sediment and water chemistry may have an adverse impact on aquatic ecosystems, such as lowered fish population (Dunham, Young, Gresswell, & Rieman, 2003), loss of spawning and rearing habitats, and loss of streamside vegetation.

3.2.3 Wildfire risk

Focusing on the state level, according to the "Wildfire Hazard Risk Report" (Botts et al., 2013; Botts, Thomas, McCabe, Stueck, & Suhr, 2015)[2], by CoreLogic Inc., there are 7,724 residential properties in New Mexico located in areas at the very high risk level, 24,663 located in the high risk category and 11,530 located in the moderate risk

[2] All residential properties in New Mexico were assigned one of the following six categories (urban property, agricultural property, property with low risk, modertate risk, high risk or very high risk). Both urban and agricultural properties were considered to have low fire risk.

category, as of 2013. The estimated reconstruction value of very high risk properties totaled $1.1 billion, high risk properties amounted to $3.5 billion and moderate risk properties is estimated to be $1.6 billion. The number of very high and high risk properties increased by 23% and 4%, respectively, between 2013 and 2015. Accordingly, the estimated reconstruction cost of properties within the moderate risk category increased by 185%, followed by properties within the very high risk category (109%) and properties within the high risk category (102%). The categorical risk measure (low, moderate, high and very high) only accounts for risk factors inside the property boundary. Besides the categorical risk measure, the research team also constructed a numerical risk score (1-50, 51-60, 61-80, 81-100), which considers risk factors both inside and outside of the boundary[3]. This trend of rapid cost increases is also detected when using the numerical risk score. The number of residential properties with a risk score of “81-100” increased from 35,024 to 39,871 between 2013 and 2015, and the reconstruction cost is estimated to rise by 108%. The number of properties with a risk score of “61-80” increased from 23,224 to 32,139 and the cost of reconstruction also increased dramatically (163%).

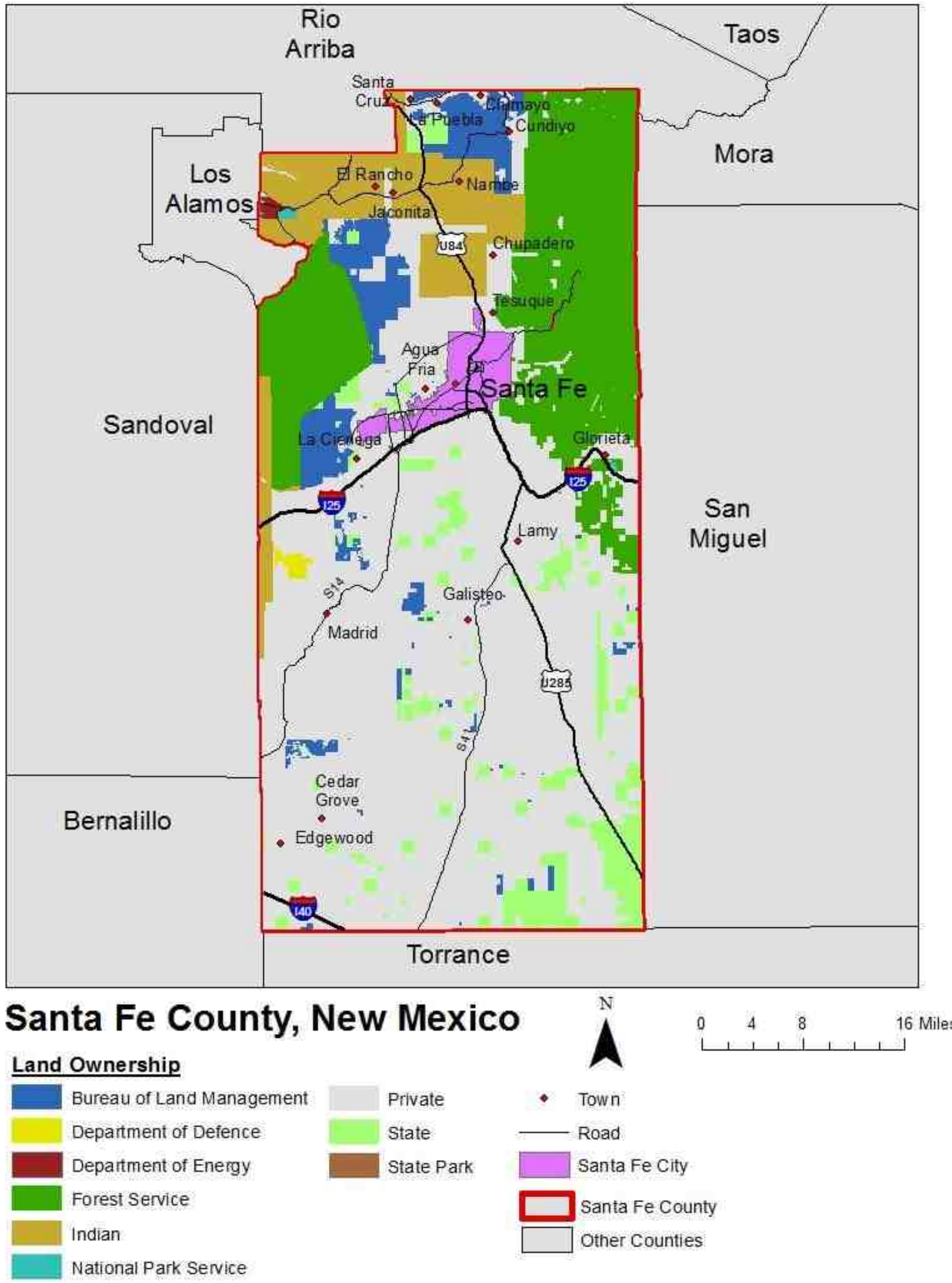
Turning from a review of the state level to the county level, within Santa Fe County there are 76,455 parcels of land (Table 3.1). According to risk assessments conducted by Santa Fe CWPP team, about 66% is at moderate composite risk from wildfire, followed by high composite risk (31%), and extreme risk (2.16%). Furthermore,

[3] All single-family residences in New Mexico were assigned a numerical risk score.

21,884 (29%) parcels are located in the WUI. Of these, 51% is in high WUI risk category, followed by moderate WUI risk (37%), very high WUI risk (11%) and extreme WUI risk (2%).

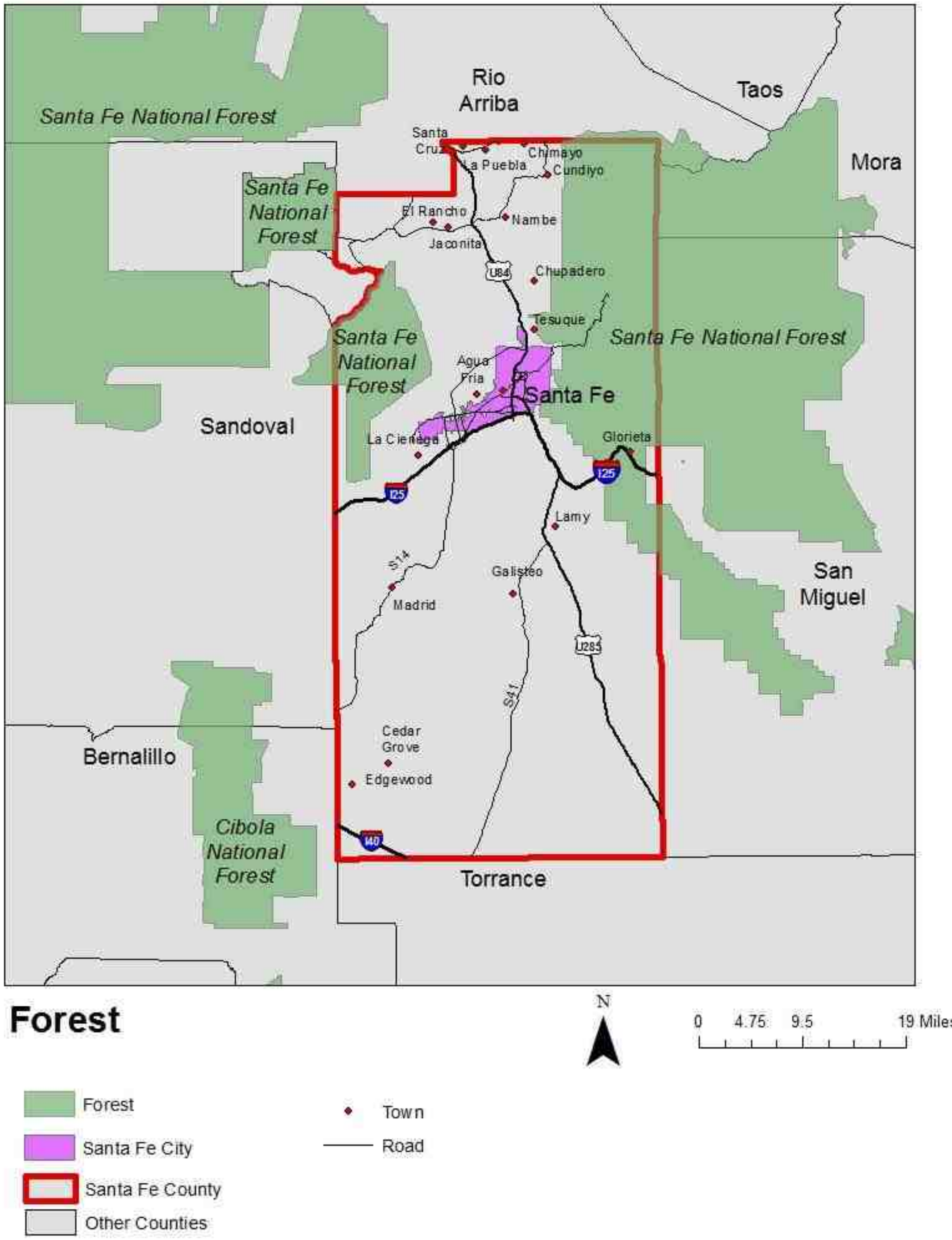
Of the 76,455 parcels, 46,413 are single-family houses (60%). One can see the distribution of single-family houses by wildfire risk is quite similar to the risk faced by all parcels. The vast majority is in the moderate composite risk category (66%), followed by high composite risk (31%). Similarly, approximately 29% of single-family houses are in the WUI. Furthermore, a slightly higher percentage of single-family houses are at high WUI risk from wildfire (55%) while moderate and very high WUI risk single-family houses are two and three percentage points lower relative to all parcels, respectively.

Figure 3.1: Santa Fe County



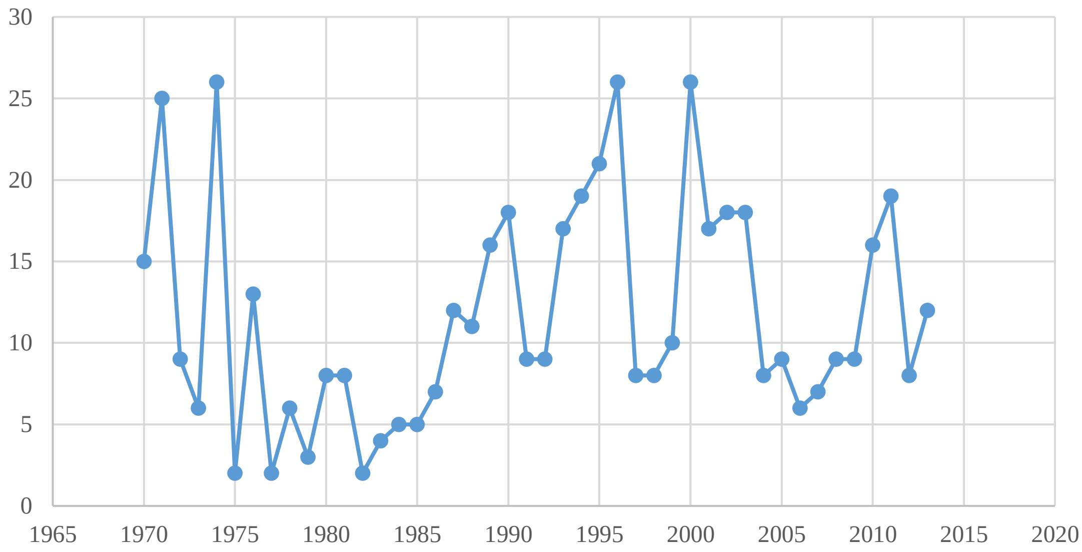
Source: constructed by the author in ESRI ArcMap 10.1

Figure 3.2: Santa Fe and Cibola National Forests



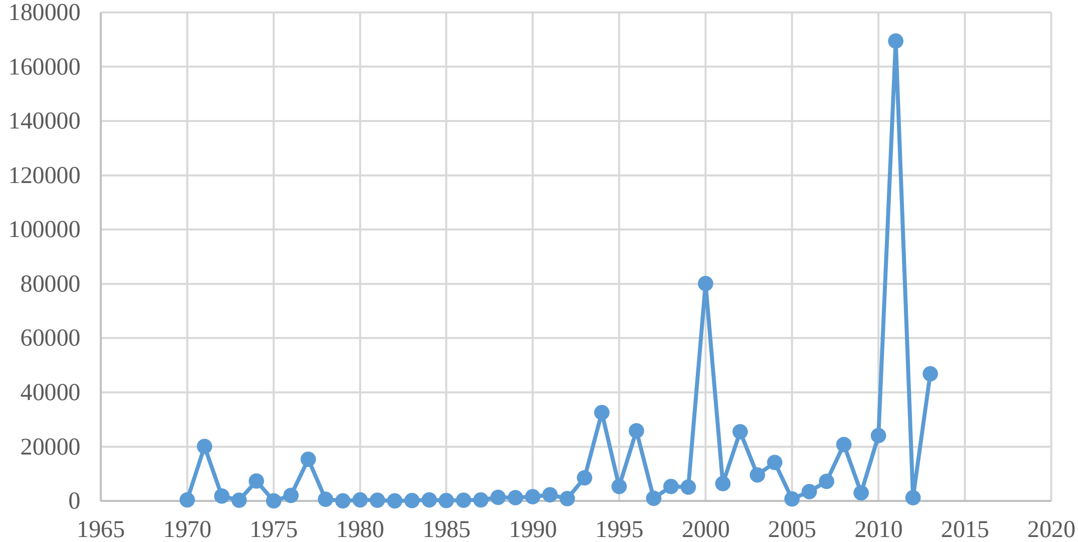
Source: constructed by the author in ESRI ArcMap 10.1

Figure 3.3: Number of fires in Santa Fe and Cibola National Forest, 1970-2013



Source: Southwestern region fire occurrence history—polygons from USDA, 2013.

Figure 3.4: Total acres burned in Santa Fe and Cibola National Forest, 1970-2013



Source: Southwestern region fire occurrence history—polygons from USDA, 2013.

Table 3.1: Parcels distribution by composite risk and WUI risk, Santa Fe County

	All land parcel (76,455)		Single-family house (46,413)	
	Frequency	**Percentage**	**Frequency**	**Percentage**
Composite risk				
Low	136	0.18%	37	0.08%
Moderate	50,621	66.21%	30,701	66.15%
High	24,045	31.45%	14,535	31.32%
Extreme	1,653	2.16%	1,140	2.46%
WUI risk				
Moderate	8,017	36.63%	4,648	34.81%
High	11,090	50.68%	7,345	55.01%
Very high	2,359	10.78%	1,059	7.93%
Extreme	418	1.91%	299	2.24%

Source: All land parcel and single-family houses data from Santa Fe Assessor's Office.

Risk data obtained from Santa Fe Geographic Information Systems (GIS) Division.

Chapter 4 Hedonic theory, functional form and spatial econometrics

This chapter will present hedonic price theory and functional forms commonly used in hedonic model. I then take into account spatial econometric techniques, including spatial autoregressive hedonic models, spatial weight matrix, tests for spatial dependence and estimation methods.

4.1 The standard hedonic pricing model

The hedonic model exploits the relationship between the price of a marketed good and the number of characteristics or attributes inherent in the good. It is a revealed preference method that measures the individual characteristic factor effects on prices, and specifically estimates the marginal implicit price of characteristics that a good possesses. This method has been widely used to evaluate non-market goods due to the fact that no explicit market exists for trading embodied characteristics in a differentiated product. For example, one can use peoples' willingness to pay for property to estimate the value of some environmental attributes that are not observable on the market, such as the effect of air quality or the proximity of a piece of property to a lake.

The hedonic model is based on the consumer theory that individuals do not derive utility from a good per se, but from the various characteristics of that good (Lancaster, 1966). A product is defined by its various attributes and collections of those attributes. One can infer the price of each particular characteristic in a product through the price of the product. The hedonic price is expressed as the "implicit prices of attributes and are revealed to economic agents from observed prices of differentiated products and the specific amount of characteristic associated with them" (Rosen, 1974, p. 34). The marginal implicit price of the individual attribute, for a market with a "sufficiently large" number of differentiated products, is defined as the changes in the price of the good for one unit increase in a given attribute.

The theoretical framework of the hedonic pricing model is formalized by Rosen (1974) in terms of an equilibrium outcome from a differentiated goods market, where the equilibrium price can be expressed as a function of a product's characteristics. Rosen characterizes the interactions of buyers and sellers through the demand decisions of customers and the supply behavior of producers. It is further assumed that customers derive utility from the characteristics associated with the good, not the good per se, and they maximize their utility by choosing from a set of available choices facing a budget constraint. At equilibrium, the price of a differentiated good is expressed as a function of number of characteristics that the good possesses, which provides a theoretical framework for hedonic pricing model.

Following Taylor (2003), a good X is defined by m characteristics vector $\underline{\mathrm{x}} = (x_1, x_2, \dots, x_m)$ and the equilibrium price P is a function of these characteristics expressed by

$$P(\underline{x}) = P(x_1, x_2, \dots, x_m) \tag{4.1}$$

Assume the consumer's utility depends two goods: X, a differentiated good, and t, a composite numeraire. Thus the consumers' objective is to maximize utility subject to a budget constraint y:

$$Max\ U\ (t, x_1, x_2, \dots, x_m)\ subject\ to\ y = t + \ P(\underline{x}) \tag{4.2}$$

Under the first order conditions, utility is maximized when the following condition is satisfied,

$$\frac{\partial \mathrm{P}}{\partial \mathrm{x}_i} = \frac{\frac{\partial U}{\partial \mathrm{x}_i}}{\frac{\partial U}{\partial t}} \tag{4.3}$$

which is the marginal rate of substitution between a particular characteristic, x_i, and the composite numeraire, t, is equal to the marginal implicit price (MIP) of that characteristic, $\frac{\partial \mathrm{P}}{\partial \mathrm{x}_i}$. Since t is a composite numeraire, the marginal rate of substitution between x_i and t measures the amount of money that the customer is willing to pay for one unit increase in the characteristic x_i, that is, marginal willingness to pay. Thus,

$$\begin{aligned} &Marginal\ implict\ price\ for\ x_i \\ &= Marginal\ rate\ of\ substitution\ between\ x_i\ and\ t \\ &= Marginal\ WTP\ for\ x_i \end{aligned} \tag{4.4}$$

The hedonic pricing model has been widely applied in the housing market given that this market complies with assumptions in Rosen's model: a competitive market with a continuum of good and perfect information. Following this framework, a house, as a differentiated good, can be viewed as a package of three main characteristics: housing structural characteristics (e.g., lot size and number of bedrooms), neighborhood characteristics (e.g., percentage of people over 65) and environmental attributes. The price of the house can therefore be expressed as:

$$P = f(S, N, E) \tag{4.5}$$

where P is property value, S is a vector of housing structural characteristics, N is a vector of neighborhood characteristics, and E is a vector of environmental characteristics.

The objective of this paper is to examine the effect of wildfire on property values, which is considered as part of the environmental characteristics E. Thus I first split E into wildfire characteristics W and locational characteristics L. Note that both the effect of the wildfire event and wildfire risk are considered, then I further partition wildfire characteristics W into wildfire events/occurrence WE and wildfire risk WR. The final expression of the model is

$$P = f(S, N, L, WE, WR) \tag{4.6}$$

The hedonic pricing model has been used to value environmental (dis)amenities, such as green space (Ready & Abdalla, 2005; Cho, Bowker, & Park, 2006; Kong, Yin, & Nakagoshi, 2007; Conway, Li, Wolch, Kahle, & Jerrett, 2010; Izón, Hand, Fontenla, & Berrens, 2010; Saphores & Li, 2012; Kolbe & Wüstemann, 2015), drinking water or water quality (Poor, Pessagno, & Paul, 2007; Anselin, Lozano-Gracia, Deichmann, & Lall, 2010), beach (Thrane, 2005; Gopalakrishnan, Smith, Slott, & Murray, 2011; Landry & Hindsley, 2011), or forest (Y.-S. Kim & Wells, 2005; Payton, Lindsey, Wilson, Ottensmann, & Man, 2008). It also has been used to estimate the value of outdoor recreation goods, such as a fishing trip (Carter & Liese, 2010; Pitts, Thacher, Champ, & Berrens, 2012), hunting permits (Little & Berrens, 2008) and ski area crowding (Fonner & Berrens, 2014).

This model has also been used to estimate the value of environmental damage and risks, such as insect infestation in forests (Price, McCollum, & Berrens, 2010; Hansen & Naughton, 2013), flood hazards (A. Morgan, 2007; Bin, Crawford, Kruse, & Landry, 2008; Bin, Kruse, & Landry, 2008; Samarasinghe & Sharp, 2010), and earthquakes (Keskin, 2008; Nakagawa, Saito, & Yamaga, 2009; Naoi, Seko, & Sumita, 2009; Uchida, Takahashi, & Kawahara, 2014).

4.2 The choice of functional form

Rosen (1974) relates the price of the good to its inherent characteristics in the model, while providing little theoretical guidance as to the choice of appropriate functional form. Given the lack of a solid theoretical basis, researchers' selection of functional form matters since it will determine the way that the price is affected by the characteristics, and thus the implicit price of the individual characteristic. A variety of functional forms have been applied in empirical estimates, including linear and non-linear forms. Four widely used forms are linear, semi-log, double-log and more flexible functional forms, particularly the Box–Cox transformations. These are discussed next.

The linear functional form is the simplest hedonic form. If arbitrage activities are feasible and costless, meaning customers can easily unbundle and repackage the characteristics after purchase, the linear form should be employed (Rosen, 1974). The linear form is expressed as

$$P = \alpha_0 + \alpha_i X_i + \varepsilon \qquad (4.7)$$

where $i = 1, 2, \ldots m$. With this functional form, the implicit price of characteristics is constant regardless of the level of attribute. For a given characteristic x_i, the marginal implicit price is simply the coefficient α_i associated with that characteristic (e.g., $\frac{\partial \mathrm{P}}{\partial x_i} = \alpha_i$). For example, the incremental value of an additional bedroom would be the same for a house with one bedroom as it would be for one with five bedrooms.

However, in most cases arbitrage doesn't hold. Thus non-linear functional forms rise where transformation of variables appears in the function. With nonlinearity, the implicit price of a given characteristic will depend on the level of that particular characteristic, as well as the level of other characteristics. One popular non-linear functional form is semi-log, where the price is transformed using the natural logarithm transformation. The semi-log functional form is

$$lnP = \gamma_0 + \gamma_i X_i + \varepsilon \tag{4.8}$$

γ_i, interpreted as semi-elasticity of the price with regards to characteristic x_i, measures the percentage change in price P for one unit increase in x_i. Thus the marginal implicit price of x_i is equal to $\gamma_i e^{\gamma_0+\gamma_i X_i+\varepsilon}$ or $\gamma_i P$. Since price P depends on the level of all other explanatory variables and the particular characteristic x_i as well, so does the marginal implicit price of x_i.

Another popular functional form is double-log, where the price as well as all continuous explanatory variables appear as a natural logarithm, expressed as

$$lnP = \varphi_0 + \varphi_i lnX_i + \varepsilon \tag{4.9}$$

φ_i is the elasticity of the price with regards to characteristic x_i and interpreted as the percentage change in price P for a one percent increase in x_i. The marginal implicit price of x_i is $\frac{\partial \mathrm{P}}{\partial x_i} = \varphi_i \frac{e^{\varphi_0+\varphi_i lnX_i+\varepsilon}}{x_i}$ or $\varphi_i \frac{\mathrm{P}}{x_i}$. For both functional forms, the estimation of implicit price requires researchers to specify the value of price and/or the interested characteristic. It is a common practice to use the mean or median price or the interested variable for the sample.

A priori restrictions are placed on the transformation parameters in semi-log and double-log functional forms. A more generalized and flexible functional form, the Box-Cox transformation, was introduced in the 1970s (Box & Cox, 1964; Halvorsen & Pollakowski, 1981).

$$P^{\theta_1} = \mu_0 + \mu_i {X_i}^{\theta_2} + \varepsilon \tag{4.10}$$

where:

$P^{\theta_1} = \frac{P^{\theta_1 - 1}}{\theta_1}$ if $\theta_1 \neq 0$

$P^{\theta_1} = ln(P)$ if $\theta_1 = 0$

The same transformation applies to θ_2. θ_1 and θ_2 are transformation parameters. The marginal implicit price of x_i is $\frac{\partial P}{\partial x_i} = \mu_i P^{1-\theta_1} {x_i}^{\theta_2 - 1}$ for $\theta_1 \neq 0$. The Box-Cox transformation is a parametric power transformation technique which involves the estimation of transformation parameters (Sakia, 1992). The transformation parameters are determined by the empirical estimation via maximum likelihood estimation or Bayesian method (Box & Cox, 1964). When $\theta_1 = \theta_2 = 0$, it is the double-log form. When $\theta_1 = \theta_2 = 1$, it yields a linear functional form. Thus linear and double-log specifications are special cases of the Box-Cox transformation. This transformation allows for flexible functional forms, such as inverse semi-log ($\theta_1 = 1$, $\theta_2 = 0$), square roots ($\theta_1 = \theta_2 = 0.5$) and quadratics ($\theta_1 = \theta_2 = 2$).

Although the Box-Cox transformation provides more flexibility, the calculation and interpretation of the marginal implicit price is obscure. Besides, Cropper, Deck, and McConnell (1988) compared the performance of various functional forms in the hedonic regression model. They find that the simpler models (e.g., linear, semi-log, double-log and the linear Box-Cox) perform best under omitted variable scenarios, while the complex functional forms (e.g., the quadratic and the quadratic Box-Cox) perform best when all explanatory variables are observed by the researcher. On the other hand, the Box-Cox transformation is not readily available in spatial econometrics (C. W. Kim, Phipps, & Anselin, 2003). Researchers have overwhelmingly adopted the simple functional forms, especially semi-log and double-log, in the subsequent literature to avoid the risk of omitted variable bias. In line with the previous literature, these two functional forms are selected in this paper.

4.3 Spatial autoregressive hedonic model

4.3.1 Spatial models

With the advance in spatial econometric techniques (Anselin & Bera, 1998; Anselin, 2013), the issue of spatial relationships has been receiving increased attention in hedonic pricing models for over 30 years. Earlier literature usually takes into account characteristics that vary spatially, e.g., proximity to forest, lake or contaminated site, while later works address this issue explicitly using spatial econometric models. Spatial dependence (or spatial correlation) is defined as “the coincidence of value similarity with locational similarity” (Anselin & Griffith, 1988, p. 241). This implies the lack of independence among data from nearby locations, which voids the common assumption of independence in statistical analysis. This “locational similarity” indicates a loss of information, and should be explicitly addressed in empirical estimation. A failure to account for spatial dependence may lead to biased estimation of parameters and the error term’s variance, as well as serious errors in the interpretation of standard regression diagnostics, such as for model selection and heteroscedasticity (Anselin & Griffith, 1988; C. W. Kim et al., 2003).

Spatial correlation can also be positive or negative. Positive autocorrelation means that nearby locations tend to have very similar values while negative autocorrelation refers to very dissimilar values for neighboring units. Spatial autocorrelation is normally positive, e.g., similar climate or housing prices for neighboring locations. Spatial correlation is analogous to time series autocorrelation but more complex. Autocorrelation is unidirectional in time dimension since only past value can affect current value, which can be corrected with a lag operator. Spatial autocorrelation is exacerbated by the multidirectional nature in that all neighboring spatial units can affect each other. Correcting for spatial autocorrelation via spatial shift operator is not feasible because the number of neighbors and observations will affect the number of operator.

In a spatial econometric model, two basic methods exist to characterize spatial relationships, suggesting sources of spatial correlation: the spatial lag model and the spatial error model. The spatial lag model assumes spatial dependence across observations of the dependent variable, while the spatial error model considers spatial dependence between the error terms. In real estate economics, clustering based on similar housing prices is widely observed. This pattern is called the adjacency effect and may be attributable to the fact that real estate professionals typically use recent house sales from nearby locations as a reference for a transaction (Can, 1992). On the other hand, omitted variables or measurement error problems would lead to spatially correlated errors (Anselin & Bera, 1998). If unobservable factors have influence on the dependent variable but are not modelled, then their impact is relegated to the error term. This spatial correlation in the error term can be explicitly addressed using a spatial error model.

In a housing market, a spatial lag process indicates housing prices are influenced by prices of nearby or neighboring homes. Thus an additional explanatory variable is specified in the spatial lag model, namely a spatial lagged dependent variable. In a traditional hedonic model, housing price is regressed on standard explanatory characteristics, as are prices of neighboring houses. A spatial lag model is outlined as:

$$P = X\beta + \rho W_1 P + \varepsilon \qquad (4.11)$$

where X is $n * k$ matrix of explanatory variables including all structural S, neighborhood N and environmental variables E, β is the $k * 1$ vector of estimated coefficients, $\varepsilon \sim N(0, \sigma)$. W_1 is the $n * n$ exogenous spatial weight matrix specifying the assumed dependence across observations. Observations considered as neighbors are represented as non-zero, or represented as zero if not neighbors. The specification of weight matrix will be discussed in detail in the following section. $W_1 P$ is the spatially-weighted average of nearby home values, which is a spatially-lagged dependent variable, as discussed above. ρ is the spatial correlation or lag parameter, indicating the intensity of spatial dependence. If the assumed dependence doesn't exist in the data, the estimated value of ρ would be insignificant. Solving (4.11) for P

$$P = (I - \rho W_1)^{-1} X\beta + (I - \rho W_1)^{-1}\varepsilon \qquad (4.12)$$

where I is the $n * n$ identity matrix， $(I - \rho W_1)^{-1}$ is spatial multipliers and can be expanded into an infinite series (Anselin, 2013):

$$(I - \rho W_1)^{-1} = I + \rho W_1 + \rho^2 {W_1}^2 + +\rho^3 {W_1}^3 + \cdots \qquad (4.13)$$

Thus the spatially-lagged dependent variable $W_1 P$ is correlated with the error term, and must be treated as an endogenous variable. This endogeneity, resulting from simultaneity (e.g., your neighbor's housing price affects you, but yours also affects your neighbors), will make the OLS estimates biased and inefficient.

Due to the multidirectional nature of spatial data, a change in an explanatory variable at one location, will not only cause the dependent variable to change at that location, but also have an indirect or spillover effect on the dependent variable at all other locations. Thus the implicit price of change in one attribute should be corrected by the spatial lag parameter ρ. In a linear hedonic model that considers no spatial effects, the indirect effect is zero and the marginal implicit price of an attribute, β_i, is equal to the direct effect.

Spatial correlation can exist in the error term, where there is one or more omitted variable and where these omitted variables vary spatially. The errors associated with any one observation is given by a spatially-weighted average of the errors from the neighboring regions plus a random error component. The spatial error model is given by:

$$P = X\beta + u \tag{4.14}$$

$$u = \lambda W_2 u + \varepsilon$$

where W_2 is $n * n$ exogenous spatial-weight matrix corresponding to the spatial-error process, λ is the spatial error operator. In the spatial-error model, the marginal implicit price of attribute x_i is still the same as regular OLS and equals β_i. OLS can provide estimates of coefficients that remain unbiased, a non-spherical error term that remains a special case. Yet bias remains in the OLS estimators for standard errors, resulting in inefficient estimations.

If both spatial lag and spatial error are present, a general spatial model allows for a spatial lag and spatially correlated errors can be formally written as:

$$P = X\beta + \rho W_1 P + u \tag{4.15}$$

$$u = \lambda W_2 u + \varepsilon$$

Earlier empirical analysis generally set $W_1 = W_2 = W$ (Donovan et al., 2007; Breustedt & Habermann, 2011; M. A. Cole, Elliott, Okubo, & Zhou, 2013). In this analysis, I also implement the general spatial model with the same weight matrix.

4.3.2 Three weight matrices

The spatial weight matrix is a basic concept that specifies spatial relationships between n spatial units. All spatial econometric models discussed above require one to specify the weights in advance, which should be exogenous and reflect the potential interactions between observations at different locations (Anselin, 2013). Formally an $n*n$ weight matrix W can be expressed as

$$\mathrm{W}_{n*n} = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1j} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2j} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ w_{i1} & w_{i2} & \dots & w_{ij} & \dots & w_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ w_{n1} & w_{n2} & \dots & w_{nj} & \dots & w_{nn} \end{bmatrix} \tag{4.16}$$

where the element w_{ij} represents the spatial dependence degree between unit *j* and *i* ($i \neq j$); if *j* and *i* are considered as neighbors, then $w_{ij} \neq 0$; otherwise, $w_{ij} = 0$. Econometricians generally set the diagonal elements to zero $w_{ii} = 0$; this prevents regions from being considered neighbors to themselves. In addition, they normally row-standardize the weight matrix by dividing the sum of all neighbor weights as $w_{ij}^s = \frac{w_{ij}}{\sum_j w_{ij}}$, with w_{ij}^s as the scaled weight. Thus the sum of each row totals to 1. Such transformation of the spatial-weight matrix is mainly attributable to the econometric difficulties with maximum likelihood estimation. The transformation also facilitates the interpretation of an averaging of neighbor values as well as making spatial parameters comparable across different data sets, where ρ can be interpreted as the autocorrelation coefficient. In line with most empirical literature, I also specify a row standardized weight matrix with the diagonal element equal to 0.

There is little theoretical guidance with respect to the specification of the weight matrix (Anselin, 2002) and therefore it largely depends on the analyst's choice and judgment. In earlier studies, weight matrices are usually constructed based on distance, contiguity or economic criteria, with the first two being the most commonly used. Contiguity weights consider whether spatial units share a boundary, and the length of the boundary while distance weights use the geographical distance between regions. Researchers are more likely to use a contiguity weights matrix for macro-level data (e.g., data collected at the county or state level). In contrast, one usually uses a distance matrix for micro data. In line with most empirical studies, I use the latter due to household-level data structure.

Two main types of distance matrices are the K-nearest neighbor matrix and the distance band matrix. The K-nearest neighbor matrix specifies the k nearest spatial units as neighbors to a particular unit, with k varying from four to eight in the literature. This K-nearest neighbor matrix structure ensures each spatial unit has an equal number of neighbors, regardless of the distance between them. One normally sets $w_{ij} = 1$ if j is neighbor to i, and otherwise sets it to 0. However, in the distance band matrix, one presets a distance band or threshold distance of value d. Regions below the specified threshold d are considered as neighbors to a given region, while regions above are not. Units can have an unequal number of neighbors for the distance band matrix structure. One can imagine that the number of neighbors would depend on the density of houses in the region. For example, houses located in an urban area would have more neighbors than ones located in a rural area. In the earlier literature, one approach to choose the distance threshold d is to ensure that each unit has at least one neighbor, which depends on the number of observations and geographic location of each unit. Given the large sample size in this analysis, it takes an extremely long time to compute the estimators. Let d_{ij} denote the distance between spatial units *j* and *i*, then $w_{ij} \neq 0$ if $d_{ij} \leq d$, and be equal to 0 if $d_{ij} > d$. There are three commonly used weights for neighbors: (1) $w_{ij} = 1$; (2) $w_{ij} = \frac{1}{d_{ij}}$; (3) $w_{ij} = \frac{1}{d_{ij}^2}$. The first weight structure assumes that each neighbor within the distance band d has the same impact. In the other two specifications, weights would decrease with distance up to threshold *d*. This allows neighbors have differential impacts; nearby units have a larger impact on price than do more distant units.

Previous literature demonstrated that the parameter estimation is sensitive to the specification of weight matrix (Bell & Bockstael, 2000). Thus I use three different weight matrices for our estimation: the four nearest neighbors, the eight nearest neighbors and an inverse-distance matrix with distance band *d = 0.5* mile. Specifically, for the nearest neighbor weight matrix structure, $w_{ij} = 1$. For the distance band matrix, I chose the inverse distance structure $w_{ij} = \frac{1}{d_{ij}}$ for the houses located within 0.5 mile.

4.3.3 Two tests for spatial dependence

With the development of spatial econometrics, various diagnostic tests have been proposed to capture spatial dependence. The tests for spatial error dependence includes Moran's I test and Kelejian-Robinson test. Anselin, Florax, and Rey (2013) classified both as diffuse tests since they are unable to suggest the proper alternative model (e.g., spatial lag model vs spatial error model). That is, they don't point to a specific alternative hypothesis. The Lagrange Multiplier (LM) test is able to test between spatial lag and spatial error models, thus has its own advantages. Anselin and Florax (1995) has a detailed discussion of the LM test: the simple LM test for spatial error, the simple LM test for spatial lag and the robust LM test for error or lag. Other LM tests involve testing for a second-order spatial dependence or joint spatial lag and spatial moving average error. The Wald and likelihood ratio tests are asymptotically equivalent to the LM test, thus they can also be applied to test spatial dependence. Moran's I and LM tests with the robust versions remain the most commonly used tests for spatial dependence, and are used to examine the presence of spatial correlation in the paper.

4.3.3.1 Moran's I test

The Moran's I test proposed by Cliff and Ord (1972) is applied to the residual from an OLS regression, which is the most widely used method to test the presence of spatial dependence. The Moran's I statistic can be written as

$$I = \frac{N}{S_0}\frac{e'We}{e'e} \tag{4.17}$$

where $S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} W$, W is an unstandardized weight matrix, e is the OLS residuals. For a row-standardized weight matrix W^s, the above equation can be simplified to

$$I = \frac{e'W^s e}{e'e} \tag{4.18}$$

since $S_0 = N$. Under the null hypothesis of no spatial dependence $\lambda = 0$, the standardized Moran's I statistics follows a standard normal distribution. The standardized Moran I statistics can be written as:

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \sim N(0,1) \tag{4.19}$$

where E(I) $= tr(MW^s)/(N-k)$, projection matrix M = I $- X(X'X)^{-1}X'$, $Var(I) = \frac{tr\left(MW^sMW^{s'}\right)+tr(MW^sMW^s)+[tr(MW^s)]^2}{(N-k)(N-k+2)} - [E(I)]^2$, tr is the matrix trace operator.

4.3.3.2 LM tests

Two standard LM tests consider the null hypothesis of no spatial dependency. The LM test for spatial error assumes no spatial dependency in the error term in the spatial error model, while the LM test for spatial lag assumes no dependency in the dependent variable in the spatial lag model. The LM error statistic with the null hypothesis $\lambda = 0$ against the spatial error dependence alternative $\lambda \neq 0$ can be written as:

$$Error = \frac{(e'W^s e/s^2)^2}{T} \sim x^2(1) \tag{4.20}$$

with $s^2 = e'e/N$ and $T = tr[(W^s + W^{s'})W^s]$. Alternatively, the LM test for spatial lag is based on the spatial lag model, with the null hypothesis that $\rho = 0$. LM Lag statistic can be written as:

$$Lag = \frac{s^2(e'W^s p/s^2)^2}{G + Ts^2} \sim x^2(1) \tag{4.21}$$

with $G = (W^s X\beta)'M(W^s X\beta)/s^2$, $M = I - X(X'X)^{-1}X'$, T is the same as earlier. Both test statistics followed a chi-square distribution with one degree of freedom. Rejection of the null hypothesis indicates spatial dependence in the error ($\lambda \neq 0$) or lag term ($\rho \neq 0$).

Although the simple LM tests have power against the incorrect alternative, they ignore the other spatial autoregressive process, and thus are likely to reject the null regardless of the true spatial autoregressive process. The simple LM lag tends to reject the null even if the process is a spatial error and the simple LM error tends to reject the null hypothesis even if the process is spatial lag. As a result, the standard tests do not provide much help in terms of distinguishing alternative models. Anselin, Bera, Florax, and Yoon (1996) addressed this problem through the robust LM tests, which are robust against the presence of the other spatial autoregressive processes. The robust LM error statistic tests the spatial correlation of errors while correcting for the presence of spatially-lagged dependent variables, and the robust LM lag test examines the correlation between the dependent variable in the presence of spatially correlated error terms. Thus the robust LM tests treat the other spatial autoregressive process as a nuisance parameter, and accounts for its effect on the likelihood. The robust LM lag statistic can be written as:

$$RLag = \frac{s^2(e'W^s p/s^2 - e'W^s e/s^2)^2}{G + T(s^2 - 1)} \sim x^2(1) \tag{4.22}$$

The robust LM error statistic can be written as:

$$RError = \frac{[e'W^s e/s^2 - Ts^2(G + Ts^2)^{-1} e'W^s p/s^2]^2}{T(1 - \frac{Ts^2}{G + Ts^2})} \sim x^2(1) \tag{4.23}$$

If the simple LM lag statistic is significant and the simple error statistic is not, then the spatial lag model is more appropriate, and vice versa. If both simple LM test statistics are significant, then the robust LM test should be used, as suggested by Anselin et al. (1996). Furthermore, if robust the LM lag test is still significant while the robust LM error test is not, then one proceeds with the spatial lag model, and vice versa. However, if both robust statistics are significant, one chooses the model with the largest statistical value.

4.3.4 Estimation method: the generalized methods of moments based on instrumental variables

As stated earlier, the presence of spatial dependence would cause OLS estimates to be problematic. Depending on the nature of the dependence, OLS estimates may remain unbiased, yet inefficient with biased standard error estimates. Even worse, OLS can provide biased and inefficient parameter estimates under some circumstances. Several methods have been applied to account for this endogeneity and/or correlated errors issue in spatial models, including the maximum likelihood estimator (MLE) (Ord, 1975), the generalized methods of moments based on instrumental variables (GMM/IV)

(Kelejian & Prucha, 1998, 1999; Anselin, 2013), and the Bayesian Markov Chain Monte Carlo (MCMC) estimator (LeSage, 1997).

The MLE maximizes the joint probability density of the given sample, assuming the error terms are normally distributed. The GMM/IV estimator use the GMM approach, the IV approach or the combination of the two to yield consistent estimates. The GMM approach assumes that the error term is independent and identically distributed and the GMM doesn't require any distributional assumption for the error term. The Bayesian estimator has been receiving more attention in recent years. This method is based on inference using Bayes's theorem. Belief about the distribution of the parameters was updated after taking the observed data into account, and researchers selected the model with the highest posterior probability. Bayesian posterior probability is the criterion to determine the appropriate weight matrix and spatial econometric models simultaneously. Nonetheless, the MLE and the GMM/IV investigate robustness of spatial econometric model with different weight matrix structures; the test for significant difference often requires nested models, such as the Likelihood Ratio test. The MLE and the GMM/IV are more commonly applied in spatial econometrics relative to the Bayesian estimator.

Generally, the MLE requires stronger assumptions to derive consistent and asymptotic normal estimator, relative to the GMM/IV approach (Lee, 2004). Another disadvantage of the MLE computation is high complexity due to the calculation of the Jacobian term, especially for large data sets (LeSage & Pace, 2009). Furthermore, the MLE yields inconsistent estimations in the presence of heteroscedasticity of an unknown form, while the GMM makes use of the moment conditions to take heteroscedasticity into account (Dogan, 2015). The GMM/IV can handle spatial models with additional endogenous variables other than the endogenous spatial lag, while the MLE cannot (Fingleton & Le Gallo, 2008).

Given the large sample size and disadvantages associated with the MLE, I use the GMM/IV approach proposed by Kelejian and Prucha (1998, 1999) in this analysis. The GMM is an estimation principle that uses moment conditions to estimate parameters. It only requires assumptions about the moments instead of the entire distribution. One can then construct the sample moment from their population analog using the observed data. The basic idea of the GMM approach is to match the sample moments and their population counterparts as closely as possible.

An initial effort to apply the GMM approach to estimate the spatial autoregressive model with autoregressive errors is reported by Kelejian and Prucha (1999), in which they demonstrate the consistency of the estimator. Furthermore, they propose a three-step procedure to estimate the general spatial model which contains spatial dependence in the dependent variable and the disturbance term (Kelejian & Prucha, 1998). In the first step, parameters are estimated using a two-stage least squares (2SLS) approach due to the presence of the endogenous spatial lag term. In the second step, to incorporate the spatial correlation of the error term, the spatial autoregressive parameter for the error term is estimated using the GMM approach suggested in Kelejian and Prucha (1999). In the third step, parameters are re-estimated by 2SLS in terms of the autoregressive parameter for the error term obtained via the second step.

Chapter 5 Data, hypotheses and systematic investigation of wildfire effects

This chapter focuses on gathering the data that are central to our questions. I first introduce the data sources, samples and variables. I then propose two hypotheses about wildfire effects. Past wildfire event/occurrence is expected to negatively affect property value whereas the effect of wildfire risk is ambiguous since risk factors that contribute to higher risk also have higher amenity value and these two have opposite effects on property value. At last, I summarize the data and econometric modelling techniques exploited in this analysis, which yield 2,000 estimated hedonic models.

5.1 Data source

Two data sources for property value were collected: assessed value and estimated sales prices. I controlled for three categories of explanatory variables in the hedonic housing model to estimate the effect of wildfires on property values. Thus this study includes three categories of explanatory variables: housing structural characteristics, neighborhood characteristics and environmental characteristics (including locational and wildfire characteristics).

5.1.1 Two data for housing prices: assessed property value and estimated house sale prices

The main challenge in gathering data for this study is the confidentiality of house sale price data in New Mexico. New Mexico is a non-disclosure state. NMSA 1978, section 7-38-4 entitled “Confidentiality of Information”, prohibits government employees from providing the sales price of any particular property to the general public; thus house sale prices are not publicly available[4]. In empirical studies, assessed values and the aggregate census data are alternatives to the actual sale prices data.

Although the use of the actual sales data in the hedonic price model is prevalent, it is not without disadvantages. The actual sale prices are based on market transactions. Potential disadvantages associated with using this data include: lack of data for markets with slow or sparse sales, biased prices due to incomplete information, manipulated transactions by real estate agents and transactions between family members (Pollakowski, 1995; Doss & Taff, 1996; Cotteleer & van Kooten, 2012; S. Ma & Swinton, 2012). When sales prices data are not desirable or publicly available, two potential alternatives, assessed value and the aggregate census data, are usually employed to capture housing values in hedonic studies.

Properties are assessed by tax offices for tax purposes periodically, typically each year. Therefore, assessed values are usually available for all properties. Compared to the actual sale prices data, the advantage of assessed data is obvious: it is usually readily available and has relatively large data size. However assessed values are affected by many factors, such as personal opinion of assessors, comparable sales and historical appraisals (Cotteleer & van Kooten, 2012). Thus, there is some controversy as to whether assessed value data is a good proxy for the actual sale prices. One hedonic study found that sale prices data better captures the value of natural amenities relative to the assessed

[4] I also contacted the Santa Fe Association of Realtors for housing sale prices. However, I didn’t obtain any data since it is against association policy to provide sales price information to the public.

data (Ma & Swinton, 2012). Other studies comparing assessed value with sale price found good overall comparability (R. Cole, Cuilkey, & Miles, 1986; Clapp & Giaccotto, 1992; Rush & Bruggink, 2000; Grimes & Aitken, 2008). For example, in a study of price indices for property values, Clapp and Giaccotto (1992) found that the measurement error associated with assessed data is negligible due to the large sample size. In addition, several studies found that assessed value results are superior to sales price results (Schuler, 1990; Janssen & Söderberg, 1999; J. Kim & Goldsmith, 2009). Kim and Goldsmith (2009) assessed the impact of swine production on rural property values using hedonic price model. They found that, the sales price data is problematic due to poor data quality and spatial abnormality of properties. Parent and Vom Hofe (2013) argued that assessed value data is more appropriate than sales price data for their hedonic analysis since the size of sale prices data, which is based on actual market transactions, is significantly reduced.

Researchers have also utilized census data on housing prices in hedonic studies (Harrison & Rubinfeld, 1978; Bair & Fitzgerald, 2005; Cho, Kim, Roberts, & Jung, 2009; Izón et al., 2010; Hanka, Ambrosius, Gilderbloom, & Wresinski, 2015). Census data report the median (or average) of owner-reported home values, which are aggregated at the census tract, block or block group level. The major concern with using the aggregate level data is "omitted factors that might be the actual source of the effects attributed to approximate measures of the site disamenities" (Palmquist & Smith, 2002, p. 7). Several studies revealed that census data is a good proxy for the actual sale prices. Kiel and Zabel (1999) found a tendency for owners to overvalue their home. However, this value is not systematically related to housing and neighborhood characteristics, and thus owners' selfreported value produce unbiased estimates. Shultz and King (2001) found little difference in model fit and the estimated coefficients between census tract level data and individual house level data. Butsic, Hanak, and Valletta (2011) utilized two data sets, census tract data and actual sale prices for individual house to estimate the impact of climate change on housing prices. Their hedonic estimation results also revealed the consistency of parameter estimates across the two data sets.

In this analysis, we collect two alternative sets of data: (1) assessed property value and (2) estimated sale prices to construct the dependent variable in the hedonic model. Assessed property values are obtained from Santa Fe County Assessor's Office. Properties were assessed annually, purely for property tax purposes. Assessors assess values using home characteristics, historical assessments and comparable sales as inputs. A New Mexico state law limits how assessors can value residential property. Law 7-36-21.2 mandates a three percent residential property value growth cap unless the property has been transferred. That is, the assessed value and the market value may be the same for properties that have changed hands within the past 10 years; for other properties the value is raised 3% annually until the market value has been reached. In spite of this limitation, assessed property values reflect the most current market information available.

Estimated sale prices are obtained from a commercial vendor, CoreLogic Inc. For non-disclosure states, their database contains comprehensive loan information, including mortgage type, amount, interest rate, lender name, maturity data etc. Using mortgage type and loan amount, CoreLogic research team infer price information (referred as estimated sale price) for each property that has transferred[5]. Although this price is based on market transaction, it is not the actual transaction price, but an estimation from the mortgage amount. At the time, we are unaware of any prior hedonic study which uses estimated sale prices. However it is a practical alternative when the actual sale prices are not available.

5.1.2 Housing structural characteristics

While pricing is restricted to assessed property values, the Santa Fe County Assessor's Office also has detailed information about housing structural characteristics. Santa Fe Assessor's office maintain a dataset including information about a home's square feet, the number of bedrooms and bathrooms, whether the house has a fireplace and central air conditioning, and the condition of the dwelling. A GIS map of property boundaries in Santa Fe County is also available from Santa Fe County assessor's Office. Using this map, the lot size of each property was calculated in square feet. I further create a point layer shapefile for each property (hereafter referred as property location point shapefile) based on the property boundaries polygon shapefile, which use the centroid of each parcel to represent the location of each property.

5.1.3 Neighborhood characteristics

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[5] For example, in some states, the sales price is computed as follows. For conventional mortgage: estimated sale price =1.33 * loan amount; for Federal Housing Administration mortgage: estimated sale price = 1.01 * loan amount; for Veterans Affairs mortgage: estimated sale price = 0.98 * loan amount.

I controlled for three census tract-level characteristics that are widely used as neighborhood features in the literature. All data were obtained from US Census Bureau, and 2009-2013 American Community Survey (ACS) 5-year estimates was used (US Census Bureau, 2013)[6]. The first is a variable that measures the level of educational attainment, the percentage of the population aged 25 and older who has a high school degree or above. I use this as a proxy variable to measure school quality since a direct measure of school quality is unavailable. Two other neighborhood characteristics, the percentage of the population over 65 years old and the percentage who are white are also included in the model.

5.1.4 Locational characteristics

I also controlled for several locational measures regarding accessibility, including the distance to the nearest highway, to the nearest industrial center (for areas classified as industry, commercial and service, I name them industry in this analysis) and to the nearest town or city. Proximity to the highway and to an economic development center are crucial factors in residential location choices. Proximity to the highway represents the level of accessibility to transportation. It may have a positive or negative effect on the property values. Improved accessibility tends to positively affect the desirability of a

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[6] The ACS counts people based on "current residence" concept, which is defined by a "two-month rule". A person is considered to be a resident of a unit if the person has lived in that unit for 2 months or more at the time of survey contact. Since the decennial census uses the "usual residence" rule, the ACS and census may result in different statistics for areas with seasonal populations.

location, thus increase property value. However, one also needs to consider the negative impact of highway traffic and noise pollution. A large body of literature found that proximity to a highway has a positive effect on property value. Distance to the location of employment is also found to have a dramatic effect on property value. Thus distance to an industry center, which offers jobs and extensive services, is also included as a measure of accessibility to employment. I also controlled for distance to the nearest town or city boundary to distinguish properties that are within the town/city boundary from those that are far away. Two environmental amenities were also controlled for: the distance to the nearest area that is classified as water (for areas classified as lakes and reservoirs, I name them water in this analysis) and to the nearest forest boundary. Research shows that proximity to these amenities tends to have a positive influence on property values.

Highway and town/city shapefiles were obtained from the US Census Bureau, 2010 data[7]. Land cover shapefile was obtained from the US Geological Survey, which maintains a website with land-use and land-cover data sets (US Geological Survey, 2014). The 2007 land cover polygon shapefile is used to identify areas classified as water, and industry. Geospatial forest boundary shapefiles are available at USDA website.[8] These GIS maps were combined with property location point shapefiles to compute the distance from each property to the relevant characteristics. All distances are calculated as the straight-line distance from the centroid of the property and measured in kilometers. For example, the distance to the nearest highway is calculated as the straight-line (and the

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[7] https://www.census.gov/geo/maps-data/data/tiger.html

[8] ttp://www.fs.usda.gov/detail/r3/landmanagement/gis/?cid=STELPRDB5202474

shortest) distance from the centroid of the property to the nearest highway. Distance to the nearest town/city is calculated as a straight-line distance from the centroid of the property to the city boundary.

5.1.5 Wildfire characteristics

5.1.5.1 WUI

I also controlled for whether the property is located within WUI area. The WUI is an area where human development and wildland meet or intermingle. There are three major components in the WUI definition: human presence, wildland vegetation characteristics (density, type and extent), and the buffer distance between human infrastructure and wildland vegetation (Stewart, Radeloff, Hammer, & Hawbaker, 2007). In the literature, human presence is usually identified through two measures: housing density and population density. The importance of the other two components of the WUI (wildland vegetation and buffer distance) are discussed but there appears to be a lack of consistency with regards to the measurement of these aspects.

The WUI area used in the analysis is mapped by Santa Fe CWPP team. When mapping the WUI for Santa Fe County, the CWPP team considered Federal Register designation of WUI as well as factors such as post-fire effects, protection of watersheds, fuel conditions and special hazards. Then the team redefined a 2008 GIS WUI map (Figure 5.1), which is updated from a 2001 GIS WUI map. Overall, 43 WUI areas were identified. The total area covered by the WUI is just over 100,000 acres.

According to Federal Register's definition, the WUI is "where human and their development meet or intermix with wildland fuel." (Glickman & Babbitt, 2001, pp. 752-753). Specifically, the WUI area must meet a minimum density of 1 housing unit per 40 acres (6.17 housing units/km^2). Additionally, two types of WUI are defined: intermix and interface. Intermix WUI refers to areas where human structures intermingle with wildland vegetation, vegetation and fuels are dominant, and must meet the minimum housing density threshold. Interface WUI occurs where human development is adjacent to wildland vegetation, typically categorized by greater housing density, normally three or more structures per acre with shared municipal services.

In the literature, researchers normally set a threshold for wildland vegetation and a buffer distance when mapping the WUI over a large area. Specifically, vegetation and fuel should be more than 50% for the intermix WUI and less than 50% in the interface WUI; areas within 1.5 miles (2.4 km) of wildland vegetation are usually categorized as interface WUI since this is roughly the average distance that firebrands can be carried ahead of a fire front (California Fire Alliance, 2001; Radeloff et al., 2005; Stewart et al., 2007; Hammer, Stewart, & Radeloff, 2009).

5.1.5.2 Wildfire event/occurrence

Geospatial wildfire event/occurrence data are available at the USDA website (US Department of Agriculture, 2013). These data contain comprehensive wildfire perimeter information for fires that burned at least 10 acres in Santa Fe and Cibola National Forest from 1970 to 2013, including fire name, fire time, dollar cost of fire, cause of fire, and fire size. The data indicate that 255 fires occurred in Santa Fe National Forest and 354 fires occurred in Cibola National Forest, respectively (Figure 5.2). Using GIS software, wildfire perimeter maps were combined with property location point shapefiles to identify wildfire events/occurrence around each house.

There are two commonly used measurements for environmental (dis)amenities in hedonic literature for estimating environmental values: one focuses on the nearest (dis)amenity (Morancho, 2003) while the other examines the overall impact of the surrounding (dis)amenities inside various distance bands (Price et al., 2010). I therefore consider wildfire event/occurrence effects on property values from two perspectives: the effects of the nearest fire burned (referred to as the nearest fire) and the effects of fire within a certain radius (referred to as the aggregate fire). Both measures have also been used to examine the effect of wildfires on property values: the nearest fire (Stetler et al., 2010) and the aggregate fire (Xu & van Kooten, 2013) (Figure 5.3). For the nearest fire measure, three variables are considered: the distance from the house to the nearest fire, time since the nearest fire burned[9], and the size of that fire. The variable of interest is the distance from nearest fire. For the aggregate fire measure, two variables are included: the number of fires burned within a certain radius and the average size of these fires. The variable of interest is number of fires burned. Both measures intend to capture past wildfire occurrence around properties, yet with different relative emphases. The first measure only considers the effect of one fire on each property, the nearest fire; the second measure generally incorporates the effect of multiple fires.

It should be noted that the literature on hedonic pricing of wildfires has specified the time window of fires prior to the sale of the house. For example, Stetler et al. (2010)

[9] For assessed value data, time since the nearest fire burned is the time lag between the time fire burned and the assessment year 2013 while for estimated sales price data, it is the time lag between the fire and the actual sale time.

examined the fires burned in the 7 years prior to the sale; Xu and van Kooten (2013) examined the fires burned in the last 10 years. It is possible that the effect of the wildfire event/occurrence depends on the specified time window. Therefore, I consider two time windows in this analysis: fires burned within the last 7 years and within the last 15 years, respectively. These two time windows are expected to capture the short- and long-term effect of wildfire on pricing. Our selection of the time windows is consistent with previous wildfire hedonic studies (Stetler et al., 2010). Hanson and Naughton (2013) examined fires burned in the last 5 years prior to the sale and fires burned in the last 6 to 20 years to distinguish the short-run and long-run effect of wildfire.

For the assessed property value data, the assessment year 2013 is used. Therefore, fires burned in the previous 7-year window are those from the year 2006 to 2012. For the longer time window of 15 years, the data are taken from the years 1998 to 2012.

For the estimated sales price data, the actual sale date is used. The beginning date of the time window starts 7 or 15 years prior to the actual sale date. However, the end date is at least 60 days before the recorded date of the house sale since the average decision to purchase a house is made two months before the actual closing date (Loomis, 2004). For example, if a house was sold on 06/15/2012, I consider fires burned from 06/15/2005 to 04/15/2012 for the 7-year time window. Fires burned after 04/15/2015 are excluded from the analysis because they are thought to have no impact on the sale price.

It is possible that the effect of the aggregate fires depends on the distance from the property to the burned area. According to the descriptive statistics of the distance from the nearest fire, the minimum distance is about 10 kilometers and the maximum distance is about 20 kilometers. To ensure that enough properties in our sample have experienced at least one fire, I start with a buffer zone of 10 kilometers, measured in increments of 5 kilometers up to the maximum buffer zone distance of 25 kilometers. Thus this yields four distinct distance bands around each property: 10, 15, 20 and 25km, respectively. Overall, the measurement of past wildfire event/occurrence is then grouped into 10 wildfire event/occurrence measures. The nearest fire measure and the aggregate fire measure (with 10, 15, 20 and 25km distance bands), combine with two time windows (7-years and 15-years).

5.1.5.3 Wildfire risk

In this paper, I utilize three types of wildfire risk: GIS-based composite risk, community hazard and risk, and wildfire risk at the individual home level (Table 5.1). These three risk assessments are conducted at county, WUI and house level, respectively. The first two assessments are compiled by the Santa Fe CWPP team while the last one is compiled by the Santa Fe County Fire Department's Wildland Fire Division.[10]

(1) GIS-based composite risk assessment

The first is GIS-based composite risk assessment, which is intended to identify areas prone to wildfire throughout Santa Fe County (hereafter referred to as the composite risk assessment). The process for this assessment is complex. Composite risk assessment is comprised of 5 input layers: flame length, rate of spread, fireline intensity, crown fire and fire occurrence. The first 4 layers were derived using GIS and fire

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[10] Detailed description of composite risk assessment and community hazard and risk assessment are available at http://www.emnrd.state.nm.us/SFD/FireMgt/documents/SantaFeCountyCWPP2.pdf.

behavior model FlamMap. Fire occurrence was developed based on the previous fire's start points. These layers were combined using a weighted overlay tool in GIS to form the composite risk assessment, with weights reflecting the relative importance of each input layer. This assessment classifies fire risk into 4 categories: low, moderate, high and extreme (Figure 5.4).

FlamMap is a computer program that models fire behavior characteristics across a landscape using constant weather and fuel moisture inputs at one point in time. To calculate fire behavior, FlamMap uses a number of GIS data layers as input files, including five required layers (elevation, slope, aspect, surface fuel model, canopy cover) and three optional layers (canopy height, canopy base height and canopy bulk density). Two additional fire behavior models, FARSITE and BehavePlus were also used to generate fuel moisture and landscape inputs files for FlamMap.

The FlamMap inputs data can be classified into three major categories: topography, fuel and weather. Topographic data (elevation, slope and aspect) are required inputs for FlamMap. The fuel model uses 40 standard fuel models defined by Scott and Burgan (2005). Proper selection of fuel models is crucial to predicting fire behavior. The general classification of fuels by fire-carrying fuel type are: Nonburnable, Grass, Grass-Shrub, Shrub, Timer-Understory, Timber Litter and Slash-blowdown. Topography and fuel inputs data used were gathered from the LANDFIRE project. Weather inputs for FlamMap mainly include three parts: wind speed, wind direction and fuel moisture, which were developed using a fire program called FireFamilyPlus and data from the remote automated weather station (RAWS). Since FlamMap calculates fire behavior using one set of wind and fuel moisture conditions, a single wind speed (20-foot wind speed at 35 miles per hour) and wind direction (prevailing wind direction) was applied to the entire study area. Similarly, a single set of fuel moisture estimates were used, including the 1-hour, 10-hour and 100-hour dead fuel components, the live herbaceous and live woody components.

FlamMap computes fire behavior characteristics for raster cells (a cell is $30m^2$) across the landscape, including 4 outputs for flame length, rate of spread, fireline intensity and crown fire. An additional layer, the fire occurrence density map, was derived based on the previous fire's start locations, specifically start locations over a 5-mile radius from 1970 to 2007. Fire ignition points were obtained from the New Mexico State Forestry Division and the US Forest Service. Using the weighted overlay tool in GIS, these five maps were then used as input layers for the composite risk assessment. To use this tool, each layer must be recalibrated to a common scale. Thus, the cell values of all input layers were converted to a scale from 1 to 4, with 1 denoting the favorite raster value that contributes to the lowest fire risk. Based on the importance of each layer, the team then weights all layers to form a composite risk assessment, with weights for flame length, rate of spread, fireline intensity, crown fire activity and fire occurrence being 15%, 15%, 10%, 15% and 45%, respectively. That is, the cell values of each layer is multiplied by the weight and then added together to produce the final fire risk. Fire risk evaluated within composite risk assessment was also classified into 4 risk categories: low, moderate, high and extreme.

(2) Community hazard and risk assessment

The second of the three risk assessments is community hazard and risk assessment, which is conducted in the WUI of Santa Fe County and is hereafter referred to as the WUI risk assessment. This assessment uses the Wildland Fire Association Hazard Assessment Form to evaluate fire risk for each community in the WUI area (see Appendix A). It aims to evaluate fire risk at the community level, and thus numeric ratings are assigned based on averages of observed characteristics in the community. Based on these ratings, this assessment classifies fire risk into 4 categories: moderate, high, very high, and extreme (Figure 5.5).

This system is comprised of two parts: fire environment and defensibility. The fire environment is defined as the surrounding conditions, influences, and modifying forces that determine wildfire behavior. It consists of three environmental components: fuel, weather and topography. Although the weather components vary in space and time, it is assumed to be constant over all communities in the County. The constant is created from the averages of northern New Mexico's worst weather conditions for fire. These conditions occur before the monsoon season, usually in April through July. The fire environment within this assessment involves evaluating three parts: fuel hazard, slope hazard and special hazards. The fuel hazard component itself is comprised of 13 models as defined by the Forest Fire Laboratory, which is further classified into four categories: no fuel, light fuels (Grass, low shrubs), medium fuels (brush, large shrubs, and small trees) and heavy fuel (timber, slash, large brush and Bosque). Slope hazard describes the steepness of a slope as well as its aspect. Slope is expressed as a value in percentage terms. Flat to mild is defined as 0-9.9%; mild to medium as 10-19.9%, medium to moderate is 20-39.9%, and moderate to extreme is reserved for measures that are 40% or greater. Special hazards consider vegetation conditions (for example, insects kill pinon and ponderosa pine, and mistletoe) as well as special topographic conditions (chimney, steep canyon and saddles).

In addition to that first part defined as the fire environment, the second part known as defensibility describes “the relative amount of difficulty that firefighters would encounter while attempting to defend a house or group of houses” (Santa Fe County, 2008, p. 37). Four aspects are considered when evaluating defensibility. First is the average access length of dead-end road, which considers bridges, turnouts, bordering fuels, turnaround space, etc. It is described in increments as less than 600 feet, 600 to 1,000 feet, 1,000 to 1,320 feet and greater than 1,320 feet. The second factor is the average structure type in the community, with flame-resistant vs. flammable roofing/siding. There is also the factor of the clearance/defensible space or firebreak around structures, which is broken down at 30 feet. Low numbers are assigned if the distance is greater, while higher numbers (indicating increased risk) are assigned as the width of the firebreak narrows. The last factor considers the availability of water in the community, with well water described as a limited water source and community water characterized as an uninterruptible water source.

Numerical points were assigned to all the characteristics discussed above; the lower the points, the lower the fire risk. The highest possible rating for this assessment is 36 points, with up to 20 coming from the fuel environment section and the remaining 16 based on defensibility. Based on the numeric points awarded, the 43 communities in the survey were assigned categorical ratings from moderate, to high, very high and extreme. Specifically, a community is considered to be at moderate fire risk if the fire environment measures < 9 and defensibility is ≤ 4, is considered to be high if the fire environment ranges from 9-12 and defensibility is in the 5-8 range, to be very high if fire the environment is between 13-15 and defensibility is between 9-1, and it is considered to be at extreme risk if the fire environment is in the 16-20 range and defensibility ranges from 12-16. Of the 43 communities in the WUI area received a hazard rating: 14 of the areas, comprising 30,060 acres, were assigned a moderate level of risk for wildfires; 20 areas totaling 35,600 acres were assigned to the high risk category; 8 areas totaling 32,130 acres received a rating of very high risk; and 1 area of 2,650 acres received the assessment of extreme risk.

(3) Individual-level house risk assessment

Following the GIS-based composite risk and WUI risk assessment, the final assessment is the house wildfire hazard assessment, which is calculated by the Santa Fe County Fire Department's wildland fire division, which was created in 2004 to address recommendations set forth in the CWPP. This assessment focuses on areas with relatively high fire risks throughout the county. House-level fire risk assessment includes four components: site hazard, structural hazard, hazard reduction behavior and the WUI risk rating for the area where the house is located (see Appendix A). Basically, forestry personnel will assess the fire risk of a particular house from the road or driveway by observing housing conditions, as well as the surrounding fire environment and defensibility. A set of 2,042 home assessments have been conducted from 2009 to 2013.

Site hazard is mainly comprised of two parts: fire environment and defensibility. Overall, the maximum total points for site hazard is 105, with 70 points for fire environment and 35 points for defensibility. Higher number represents higher risk from wildfire. Fire environment is defined through answers to eight questions: the type of trees and ground cover within 30 feet of the house, the proximity of ground fuels to the house, the existence of ladder fuel, the slope of the house, the location of jackpots (firewood, debris or combustibles) and flammable materials (gas cans and grills, pesticides), and external hazards such as outbuildings or propane tanks. Defensibility considers the length and width of the driveway, the length of overhead branches, road slope, presence of inadequate surface/bridge, whether the house has a locking gate and the visibility of the house from road.

Structure hazard assesses the relative resistance to wildfire of the building based on its design and construction materials. The total possible points for structure hazard is 45, with two attributes (roofing material and type of foundation) comprising 55% of the average observed hazard. The other three attributes considered are the exterior walls material, vents and eaves, the presence of attachments and fuel traps (under steps, foundation indents), with 5 possible points for each.

This assessment also considers hazard reduction activities done near the house to reduce fire risk. These can be aimed at reducing fire risk on site, to the structure as well as other activities, such as the availability of firefighting equipment. On example of reducing risk would be to remove ladder fuels within a 30ft perimeter to reduce the risk of crown fires. Doing so would lower the fire risk rating by a point. The total possible points for hazard reduction is -15, which makes up 10% of the total home risk assessment. This assessment also takes into account WUI risk rating where the house is located, with 5 numerical ratings denoting the relative risk: 5 points for low risk, 10 if moderate, 20 for high risk, 30 for very high risk and 35 for extreme.

5.2 Variables and descriptive statistics

The estimated sale prices for 17,710 houses were obtained from CoreLogic Inc. covering 1993 to 2013[11]. The most recent assessment of property in 2013 was used and this yielded 52,793 properties. After deleting properties whose data had missing or inaccurate prices, or missing structural and geospatial data, I were left with 14,168 and 48,246 observations for estimated sales price and assessed property value, respectively. I limit our sample to single-family houses. I further limit the sample to houses with at least one bedroom and one bathroom, and exclude the top 1% of the sample based on the number of bedrooms (that is, houses with more than eight bedrooms in sales price data and houses with more than nine bedrooms in assessed value data).

For the estimated sale price data, I also exclude transactions with sale prices well below the market, which may be due to unusual loan amounts or transactions between family members. As a result, after consulting with the state assessors, I excluded houses valued at less than $85.8 per square foot (the lowest 10%)[12]. I were left with 10,639 transactions. For assessed property value data, I excluded houses with assessed value per square feet less than $32.50 (the lowest 1%). This yielded 41,004 houses. In addition,

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[11] About 33% of properties were sold twice during the study period. However, I only included the most recent transaction in the analysis since the first transaction data is subject to the following problems: (1) the mortgage amount used to derive estimated sale prices could not be confirmed; (2) the sale date is not available; (3)the sale date in the first transaction is really close to the sale date in the recent transaction.

[12] This cutoff seems reasonable. From 2003 through 2013, the annual average sale price per square foot ranges from $169 to $251 (Sacks, 2014).

estimated sale prices, which are available from 2003 to 2013, were adjusted to 2013 dollars using the Federal Housing Finance Agency's Housing Price Index (HPI). Since assessed values for the year 2013 are used, this makes estimated sales prices and assessed values directly comparable.

I test multicollinearity of the explanatory variables via VIF scores. The VIF values of OLS models are below 4, indicating no problem of multicollinearity. All variables used in the hedonic models are defined in Table 5.2. Categorical variables were recoded into a set of dummy variables with one category omitted. There are three housing cooling systems, central air (*Aircond*), evaporative system (*Evapcool*), forced cool air, package unit or window units (*Othercool*), and none were omitted. There are four composite risk categories: low, moderate, high and extreme. Given an extremely small number of houses are at low composite risk (less than 0.1%), I merged the low rating with the moderate rating. Thus there are two categories for composite risk, *Comp_high*, *Comp_ext*, and low/moderate which is omitted. The WUI risk ratings categories are *WUI_high*, *WUI_vhigh*, *WUI_ext* and the moderate risk rating, which is omitted. For estimated sales price data, sale years, ranging from 2003 to 2013, is represented by ten dummy variables *Yr2004, Yr2005, Yr2006,* etc. where *Yrxxxx* indicates a sale in year xxxx. The omitted sale year is 2003.

Table 5.3 and Table 5.4 provides summary statistics for estimated sales price data and assessed value data, respectively. The average estimated sales price is about $361,370, which is found to be higher than the average assessed value of $314,805. Further, the median estimated sales price value is $297,324, consistent with the median home value reported by Zillow in 2015. The median assessed property values is somewhat lower, at $222,488.

With respect to housing characteristics, they are very similar across the two sets of data. Square footage of the average house is between 1,985 and 2,134 square feet for estimated sales price data and assessed value data, respectively, and reflective of size of a single family house. However, the homes seem to have a relatively large average lot size, 61,576 and 127,588 square feet, respectively. Furthermore, the average house has 3.2 bedrooms and 2 bathrooms. A larger majority of properties has fireplace, about 70 percent. A majority of houses don't have any cooling system. Take the example of estimated sales price data, only 16 percent of houses have forced cool air, either as a package unit or window units, followed by evaporative system (14%) and central air system (10%).[13] There is variation in the physical conditions of the properties, ranging from low, fair, average, good, very good, excellent, to highly improved status. Overall, the dwelling condition of the average house is approximately 3.7, which falls between average and good condition.

Neighborhood characteristics are also very similar across the two data sets. In a typical census tract, approximately 20% of the population were over age 65, 87% identify themselves as white, about 90% of the population over 25 years old has received a high school degree or above.

[13] Percentages were rounded to the nearest whole number, which may not total to 100 exactly.

Concerning locational characteristics, the average house is about 1.25 km from the nearest highway, 0.5 km from the house to the nearest town/city boundary, 5 km from the nearest industry center. It also seems that houses are relatively far away from environmental recreational areas, 9 km from the water boundary and 5 km away from the forest boundary.

A small but significant share of houses is located within the WUI (24% for estimated sales prices data and 28% for assessed value data), which are similar to the percentage of all single-family houses located in the WUI (29%). First let's consider the nearest fire burned within the last 7 years for each property. The average house is about 20 km away from the nearest fire. The time since the nearest fire burned is approximately 58 months (4.75 years) for estimated sales price data, while there is a much shorter time interval for assessed value data, about 19 months (1.6 years). There is also variation in the size of the nearest fire. The average size of the nearest fire is 4,570 acres for the estimated sales price data and 6,272 acres for assessed value data, respectively. If one considers the nearest fire burned in the last 15 years, the following changes are notable. The distance between the house and the fire becomes shorter, 11km for estimated sales prices data and 13km for assessed value data. As expected the time lag becomes longer. The average size of the nearest fire now becomes much smaller, ranging from 639 acres to 1,577 acres.

For the aggregate fire measure, first I see that the number of fires that burned within a specific distance band for the estimated sales price data is higher than that for the assessed value data, except for the 25km radius with the 15-year time window. Secondly, I see that both the number of fires and the average size of the fires that the house experienced increased as the radius of the buffer zone increases, as one would expect. Take the example of estimated sale price data with 7-year time window, average fire size increased from 68 acres for the 10km radius, to 334 acres for the 15km radius, to the 1259 acre for the 20 km radius and to 2,859 acres for the 25km radius.

The distribution of single-family houses with regard to the three risk ratings were also similar across the two data sets. A larger share of houses is located in the low or moderate composite risk zone (63% and 67%), followed by the high composite risk zone (35% and 31%) and the extreme risk zone (2% and 2%) (Figure 5.6 and Figure 5.7). With regard to the WUI risk, the largest share of houses (60% and 56%) were located in the WUI and identified as being at high WUI risk, with an additional 33% or 35% identified as being at moderate WUI risk (Figure 5.8 and Figure 5.9). The distribution of single-family houses by wildfire risk in the two data sets are quite similar to the risk faced by all single-family houses in the county. The average individual-level house risk score is 77.4 for the estimated sales price data and 79.2 for the assessed value data; the maximum risk rating is also quite similar across the two data sets. The distribution of single-family houses with regard to individual-level house risk are shown in Figure 5.10 and 5.11.

5.3 Hypothesis about wildfire effects

In this paper, I examine the effect of wildfire on property values, specifically wildfire event/occurrence and wildfire risk. Thus our hypothesis is twofold: part 1 concerns the effect of wildfire event on property values; part 2 focuses on the effect of wildfire risk.

5.3.1 The effect of wildfire event/occurrence: negative

Previous wildfire hedonic studies generally found wildfire events would decrease property values (J. Loomis, 2004; J. Mueller et al., 2009; Stetler et al., 2010), with two studies having found mixed effects depending on the distance from the fire and the size of the fire (Hansen & Naughton, 2013; Xu & van Kooten, 2013). In line with these previous empirical studies, I hypothesize that wildfire events have a negative effect on property values.

I construct two different measurements of wildfire event/occurrence: the nearest fire and the aggregate fire, with different variables describing each term. Specifically, the nearest fire measure consists of three variables: the distance from the nearest fire, the time since the nearest fire burned (measured in months) and the size of that fire. I expect property values increase with the distance from nearest fire increases. In other words, proximity to wildfire has a negative effect on property value.

For the aggregate fire, I also hypothesize a negative relationship. Since the aggregate fire events is measured using the number of fires burned and their average size within 10, 15, 20 and 25km of the house, I expect that property value decrease as the number of fires burned near the property increases. That is, frequent wildfires decrease property value. It is also hypothesized that both effects would decay as the radius of the buffer zone increases. The economic impact would be greater for fires that burned near the house and diminish as the radius increases.

5.3.2 the effect of wildfire risk: ambiguous

There is no a priori expectation on the relationship between wildfire risk and property value given that factors contributing to high fire risk also have high amenity value (e.g., a forested view) and these two have opposite effect on property values

(Donovan et al., 2007). Amenities are expected to increase property value while wildfire risk is supposed to decrease property value. Therefore, the effect of wildfire risk is ambiguous.

The composite risk assessment is conducted throughout Santa Fe County, which includes both the Non-WUI and the WUI areas. One potential way to evaluate the effect of composite risk is to further segment the data by property location: the Non-WUI vs WUI. I hypothesize that people who live in the Non-WUI areas value amenities more, while in the WUI areas people are more concerned about wildfire risk. I may find, for example, that the positive effect of amenities dominates in the Non-WUI and therefore the risk rating has a positive effect on property value; in the WUI, the negative effects of fire risk may offset, or even outweigh the positive effect of amenities and therefore result in a nonsignificant or negative relationship. Thus, one should expect different wildfire risk effects on house pricing across geographic areas. Therefore, for models using the composite risk, I run further models according to geographic area, which generates three separate regressions: models covering the whole County, models covering the Non-WUI and models covering the WUI. The Non-WUI model is the Santa Fe County model fitted only to homes located in the Non-WUI, while the WUI model is the Santa Fe County model fitted only to homes in the WUI.

Overall, I hypothesize a positive relationship between composite risk and property value for Santa Fe County in the Non-WUI area, but a negative or insignificant relationship between wildfire effect and property value for the WUI area. Thus the effect of composite risk varies by geographic area.

5.4 Systematic investigation of wildfire effect: 2,000 specifications

This paper employed divergent measures of property value, wildfire event/occurrence and risk, and a variety of empirical modeling techniques to investigate the effect of wildfires. Table 5.5 summarizes these measures and empirical models. Specifically, two dependent variables, 10 measures for past wildfire event/occurrence, three wildfire risk measures (with three geographical areas for composite risk), four spatial dependence structures with three weight matrices, and two hedonic functional forms produce 2,000 specifications for hedonic price models[14].

5.4.1 Data feature

Data source for housing prices: Two data sets are used to measure housing prices in hedonic model: assessed value and estimated sales price. In this analysis, 1,000 models used assessed value data and 1,000 models used estimated sales price data.

Past wildfire event/occurrence measure: The effect of past fire event/occurrences is measured in two ways: the nearest wildfire or the aggregate fire for each property. The nearest fire captures the effect of the nearest fire for each property; the aggregate measure captures the surrounding fire within a certain radius. It is possible that the effect of a past

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[14] Overall, I have $the\ number\ of\ models\ =\ 2 * 10 * 5 * 10 * 2 = 2{,}000$. The first term 2 denotes 2 data sets for housing prices: assessed value and estimated sales price; the second term 10 denotes 10 measures for wildfire event/occurrence; the third term 5 denotes 3 risk measures (with 3 geographic areas for composite risk rating: Santa Fe County, the non-WUI and the WUI); the fourth term 10 denotes 10 spatial model specifications (OLS, 3 spatial autoregressive models with 3 weight matrices), the last term 2 denotes 2 functional forms (semi-log and double-log).

fire event/occurrence depends on the time window of fires prior to the sale, and therefore I incorporate two different temporal windows: 7 years and 15 years. The 7-year time window considers fire burned in the last 7 years while the 15-year time window considers fires burned in that time frame. Furthermore, I specify four buffer zones for models using the aggregate fire measure: 10, 15, 20 and 25km radius. Overall, the nearest fire measure and the aggregate measure (with those 4 radius), each with two temporal windows yield 10 wildfire event/occurrence measures. Of the 2,000 estimated hedonic models, 400 cases use the nearest wildfire measure, with 200 instances using the 7-year time window and 200 using the 15-year time window. The remaining 1,600 instances all use the aggregate measure, also evenly split: 800 instances use the 7-year time window and the other 800 use the 15-year time window.

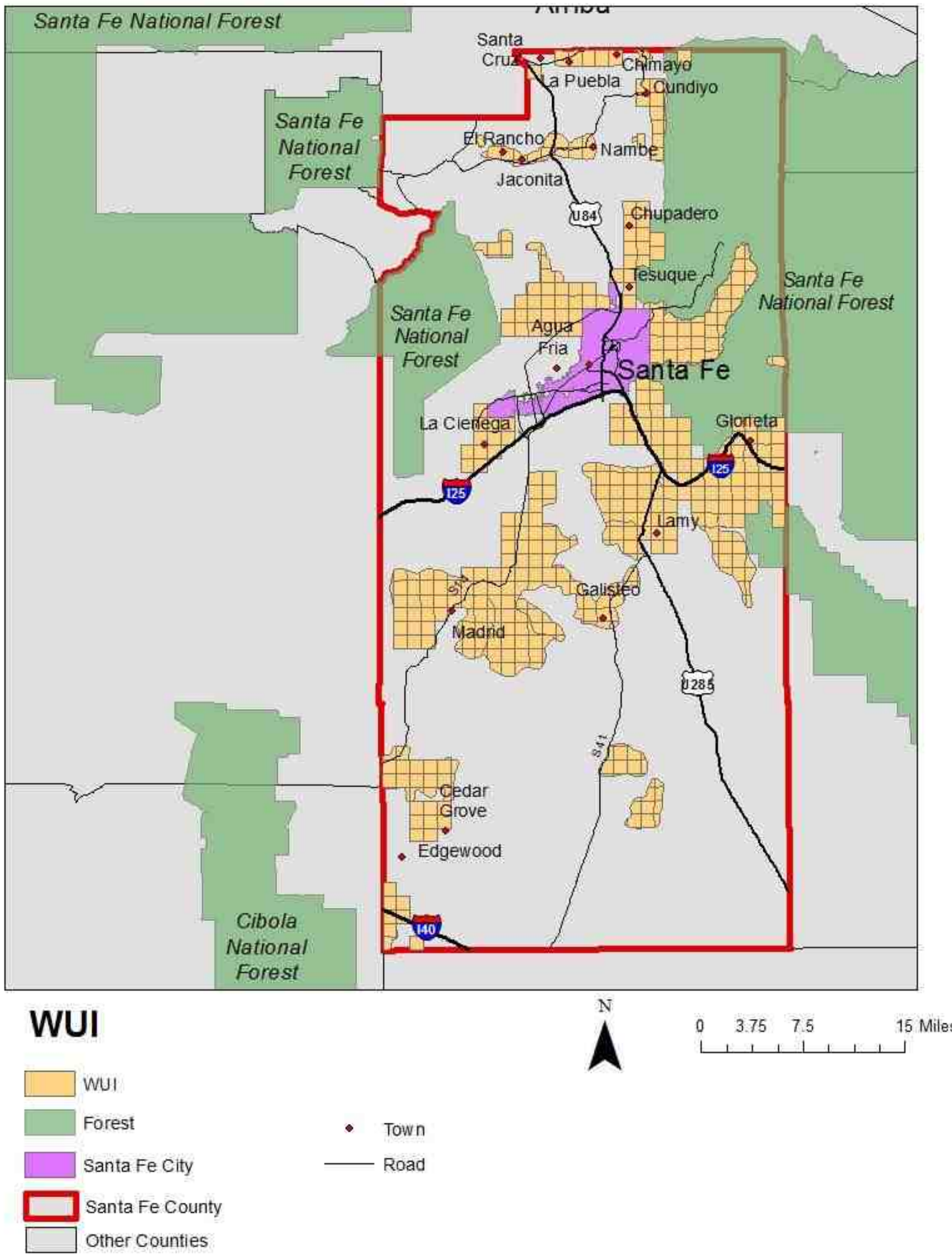
Risk measure: Three measurements for wildfire risk are incorporated in this analysis: composite risk, WUI risk, and house level risk. Composite risk rating is conducted throughout Santa Fe County while the latter two assessments focus on the WUI within the county. It is hypothesized that homeowners' perception of composite risk might vary between the Non-WUI and the WUI, as described in detail earlier. Thus for models using the composite risk, I run further models with three geographic areas: Santa Fe County, the Non-WUI area and the WUI area. In this analysis, 1,200 models were created using composite risk, 400 models were created with WUI risk and 400 more were formed through the use of house level risk. Of 1,200 models using composite risk, 400 covers the whole county, 400 covers the Non-WUI area and 400 covers the WUI area.

5.4.2 Modeling techniques

Functional form: I employ two commonly used functional forms in hedonic literature: semi-log and double-log specification. 1,000 models utilized semi-log and 1,000 models exploited the double-log functional form. For the double-log models, five explanatory variables were log-transformed: house square feet (*Area*), property lot size (*Land*), the distance to the nearest highway or state highway (*Highway*), the distance to the nearest fire (*Dist*) and the size of that fire (*Size*).

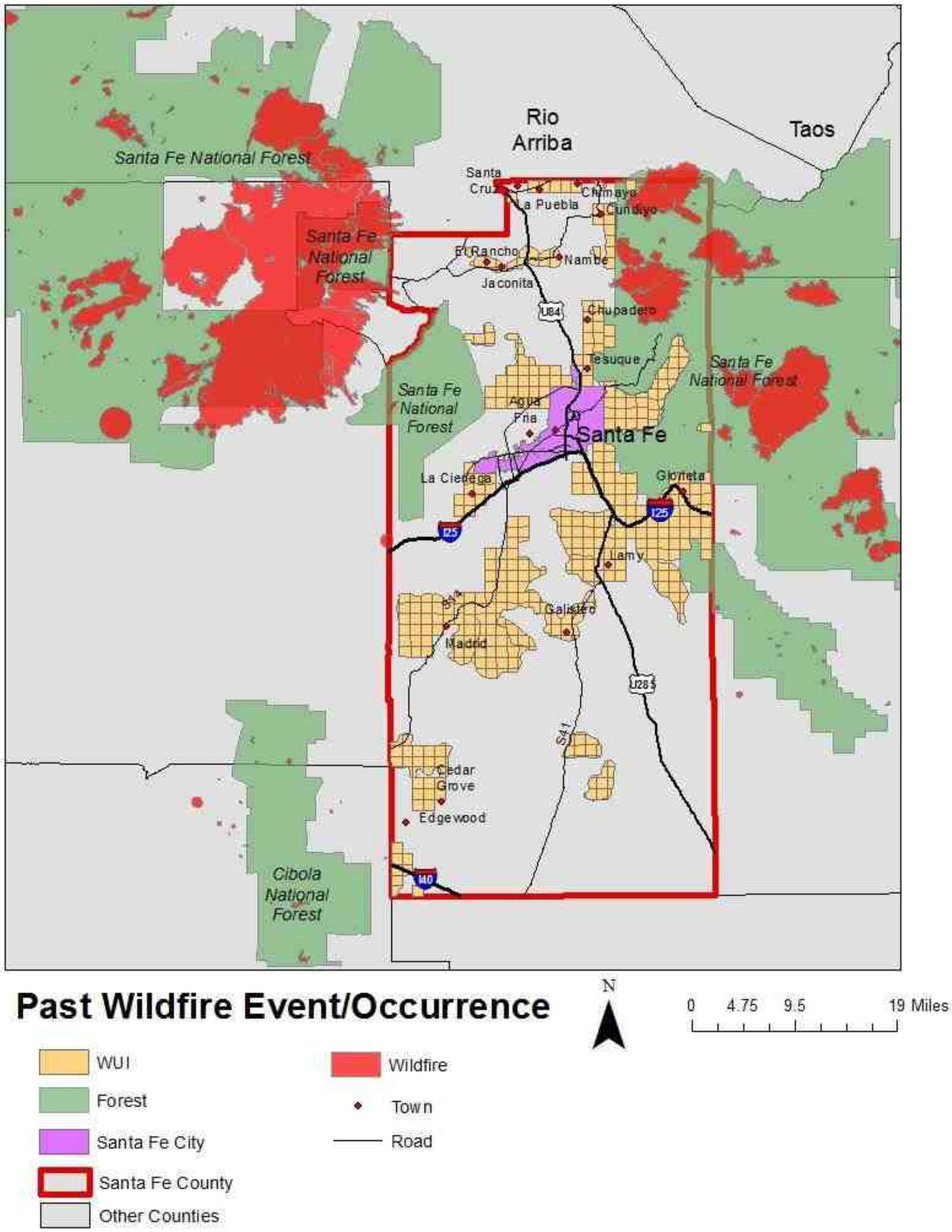
Spatial correlation: A variety of model specifications were considered. First I apply the standard hedonic price model to examine the effect of wildfire, which doesn't take spatial correlation into account. Further, I consider three spatial autoregressive models: spatial lag, spatial error and their combination, the general spatial model. For each spatial autoregressive model, three types of weight matrices were considered: the four nearest neighbors, the eight nearest neighbors and the inverse-distance weight matrix with the 0.5-mile cutoff. Overall, the OLS model, three spatial autoregressive models with three weight matrices yield 10 model specifications. Of the total 2,000 models, there are 200 OLS models and 1,800 spatial autoregressive models, which are equally distributed across 3 spatial autoregressive models and 3 weight matrices.

Figure 5.1: WUI map, Santa Fe County



Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.2: Wildfire event/occurrence in Santa Fe and Cibola National Forest, 1970-2013



Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.3: The measurement of past wildfire event/occurrence

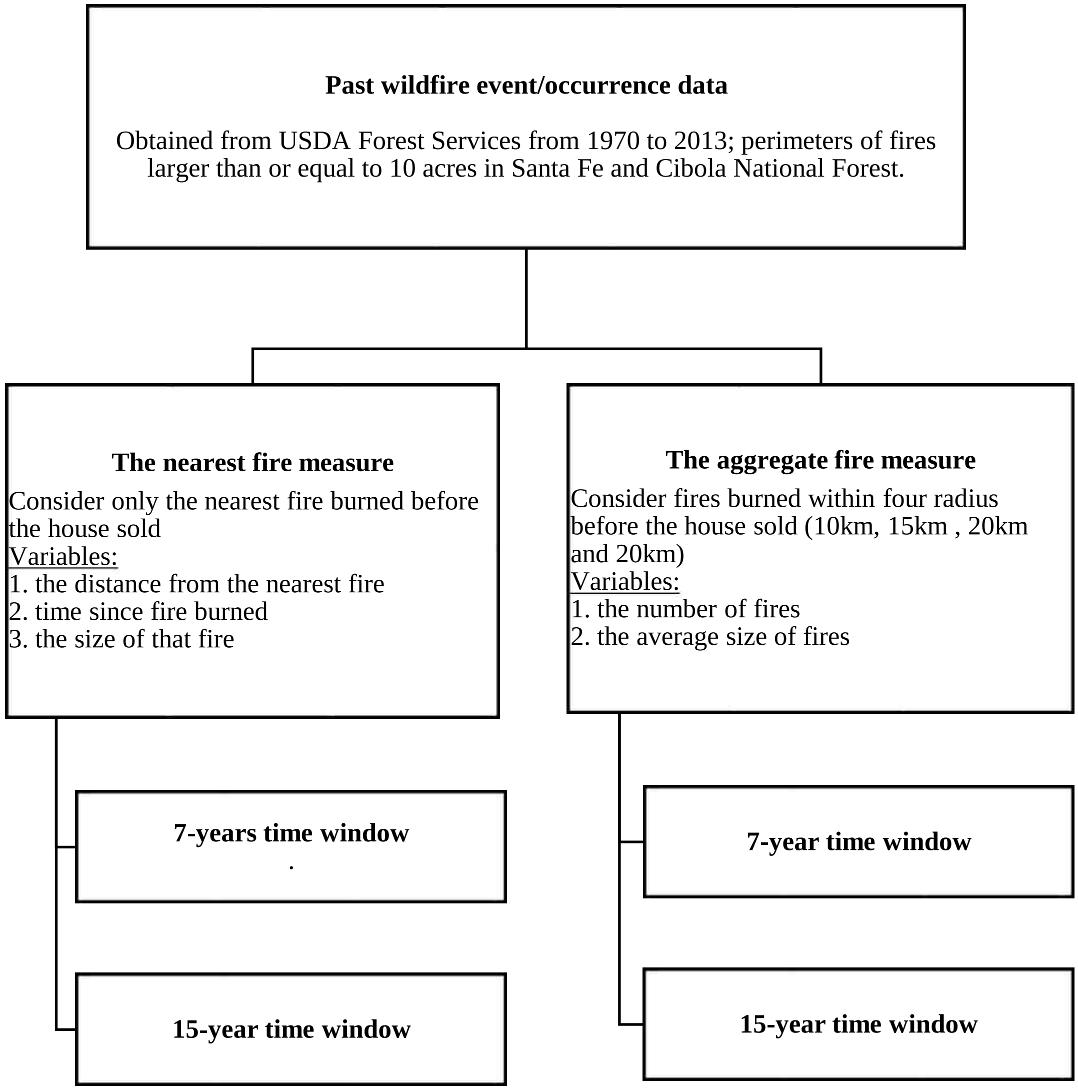
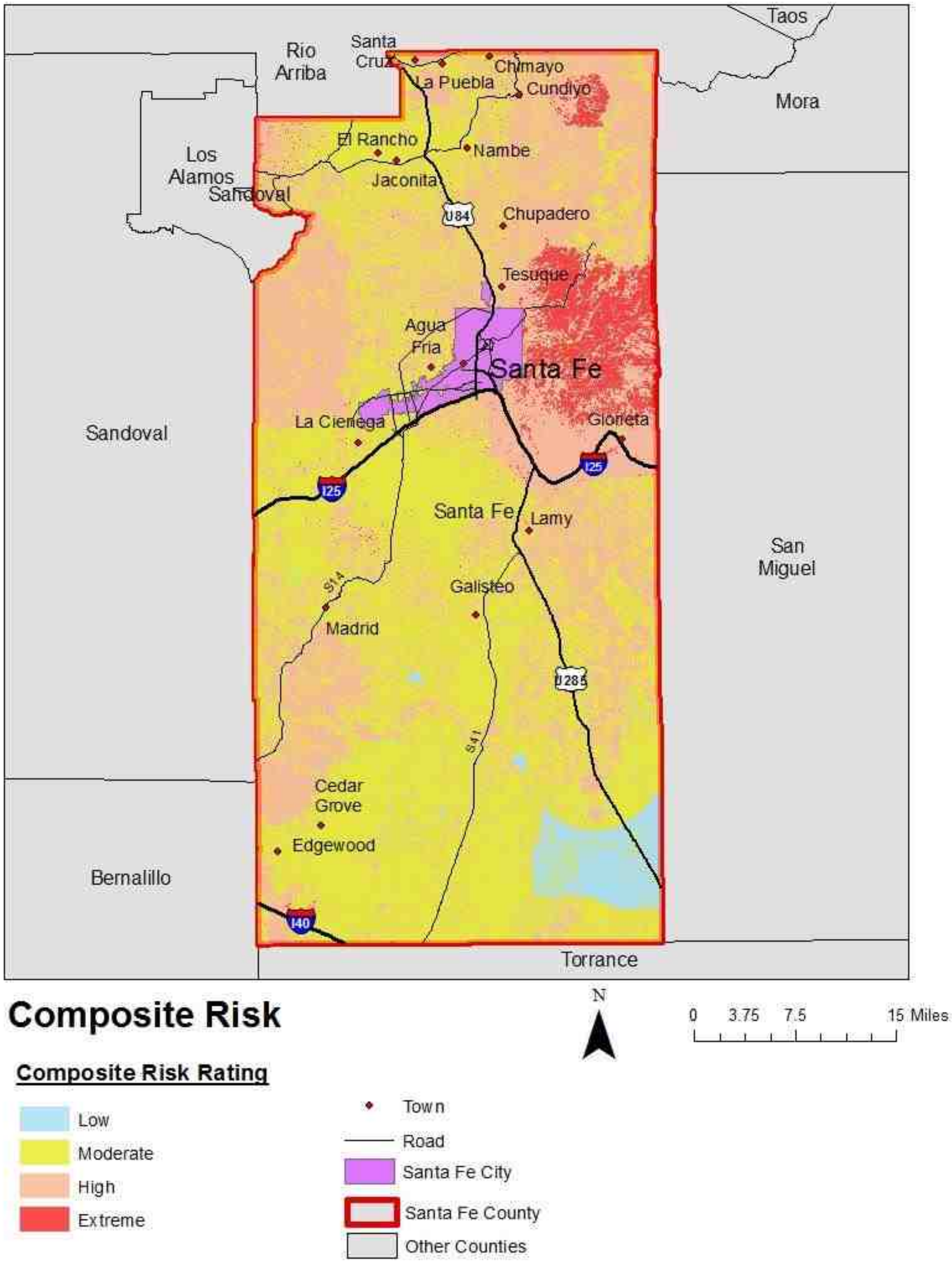
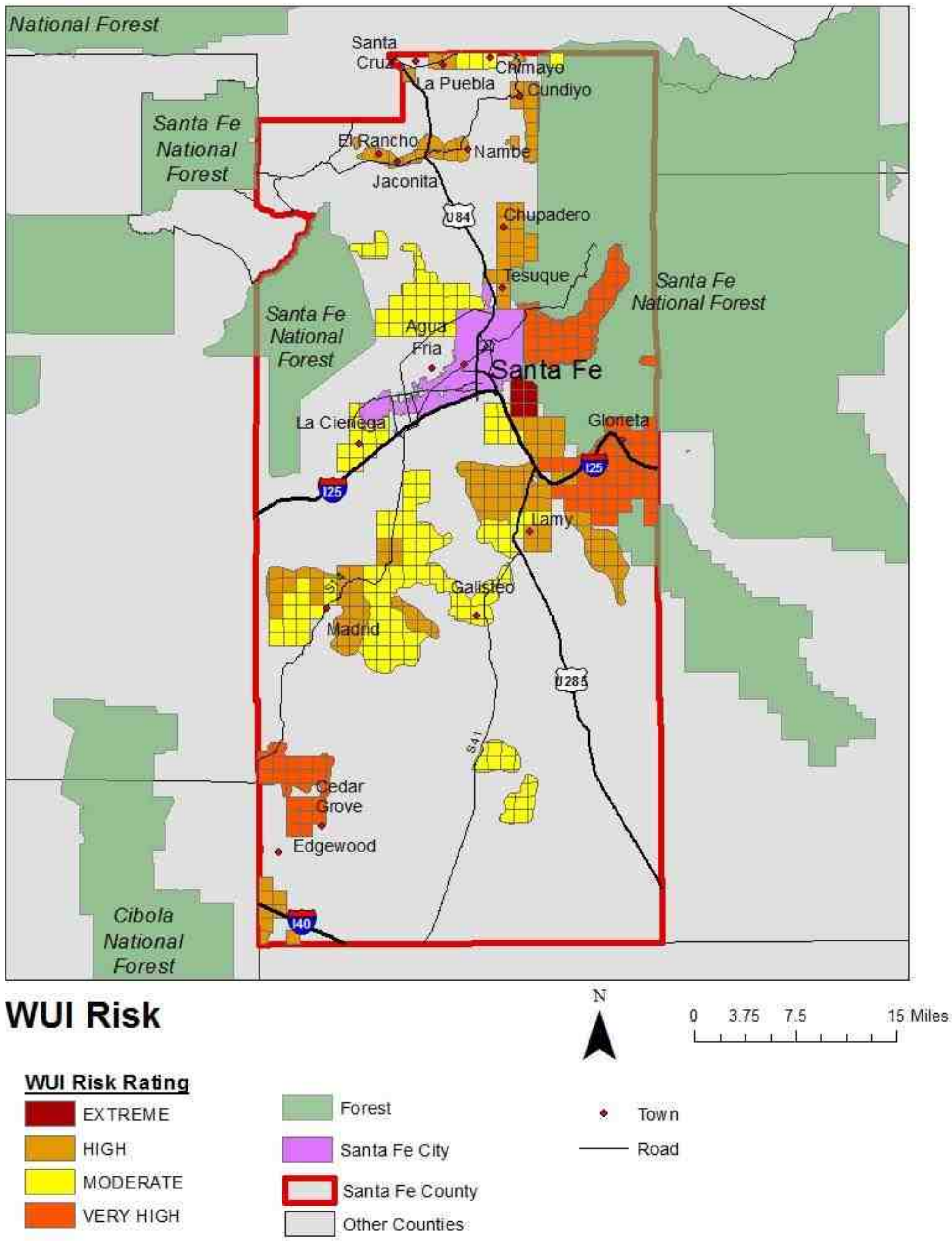


Figure 5.4: Composite risk rating, Santa Fe County (2007)



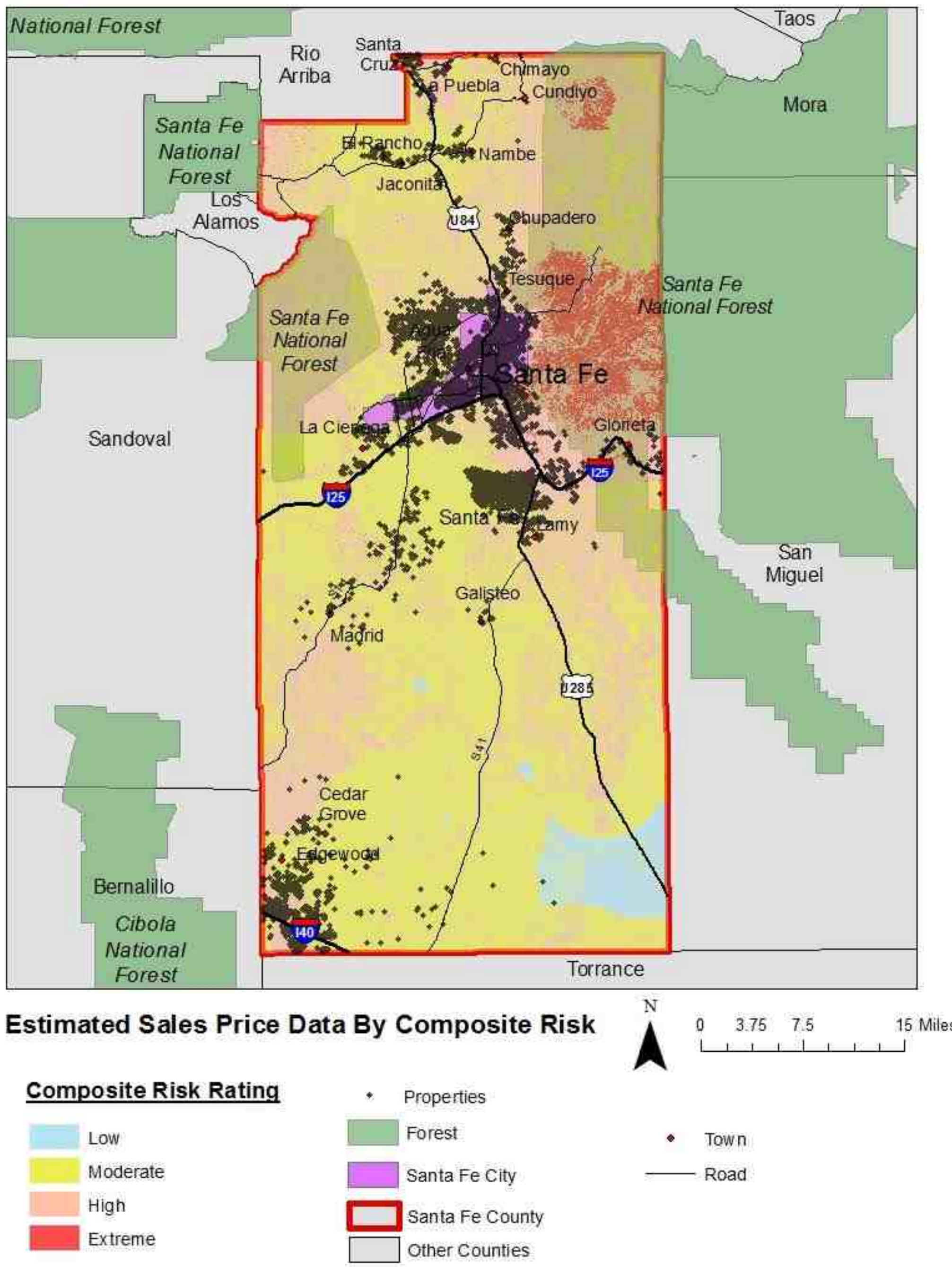
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.5: WUI risk rating, Santa Fe County (2007)



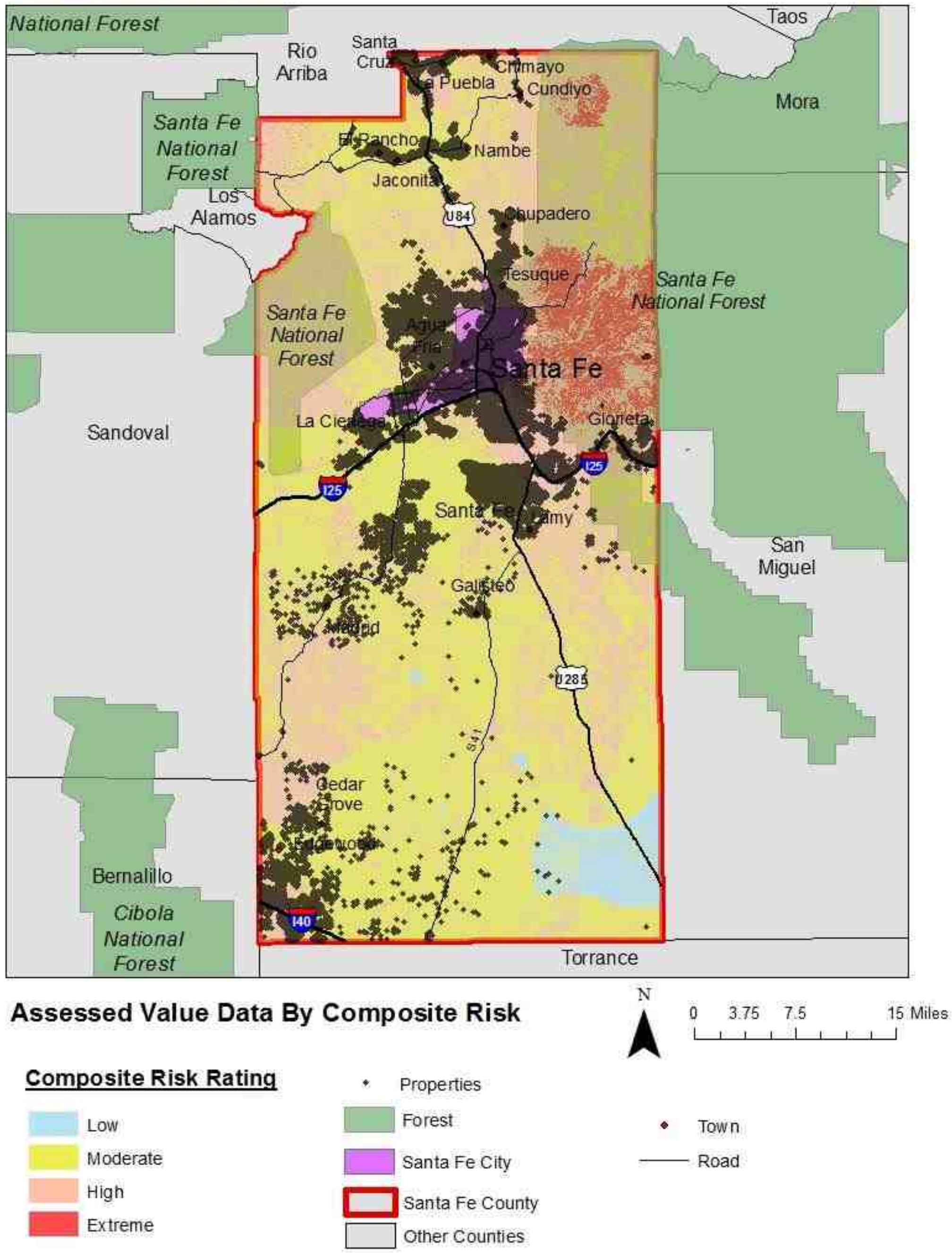
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.6: The distribution of single-family houses with regard to composite risk in estimated sales price data



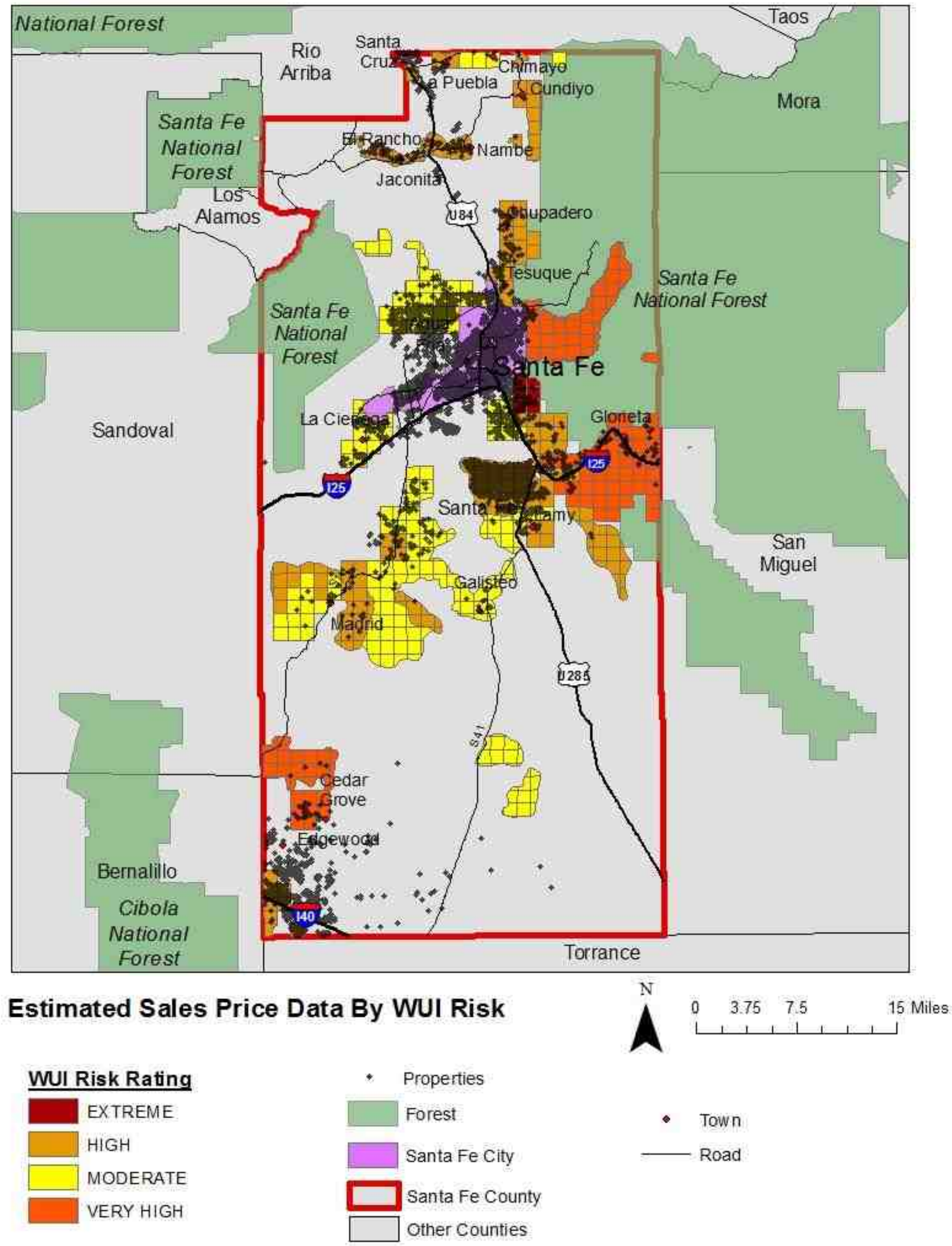
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.7: The distribution of single-family houses with regard to composite risk in assessed value data



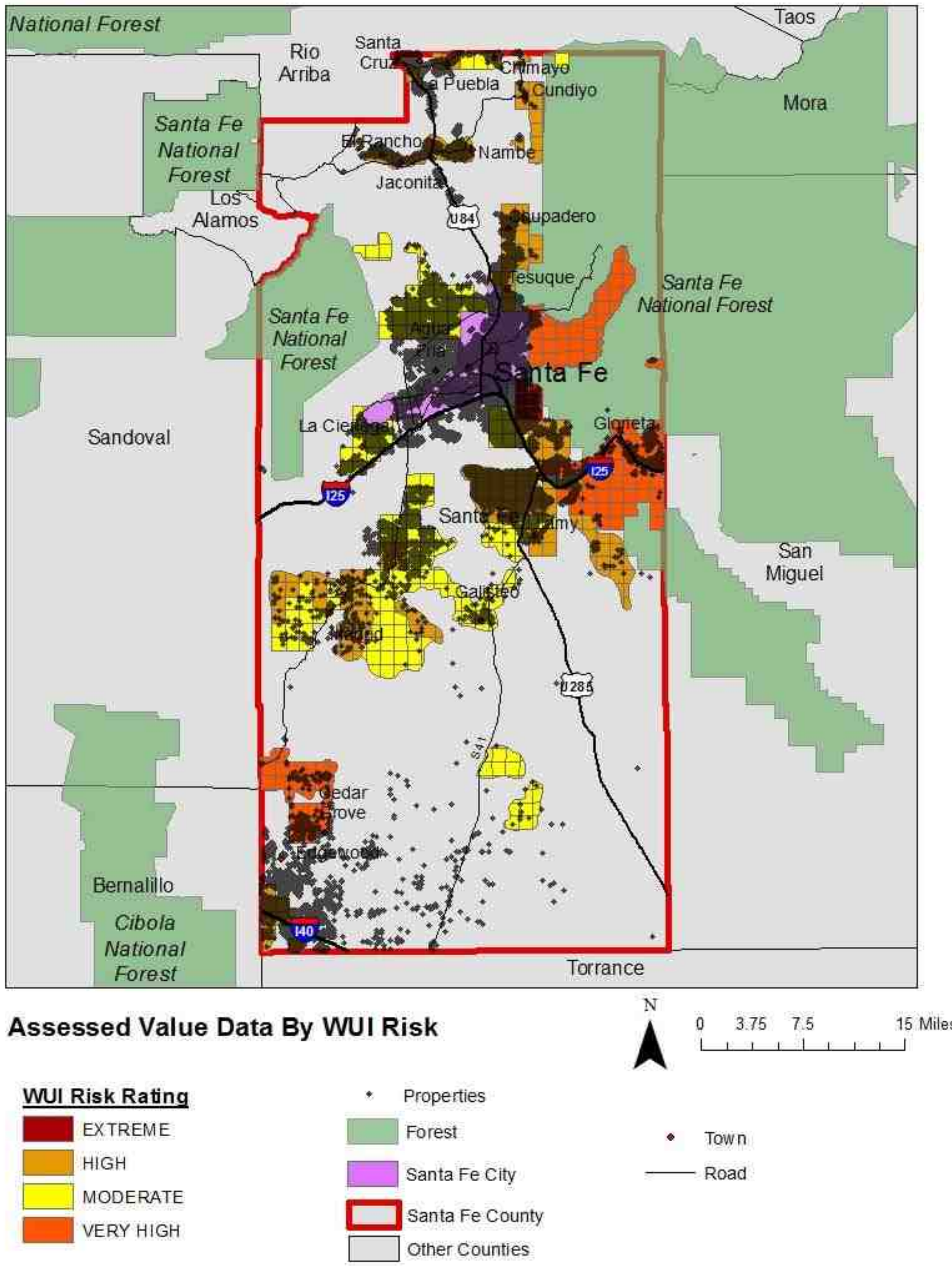
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.8: The distribution of single-family houses with regard to WUI risk in estimated sales price data



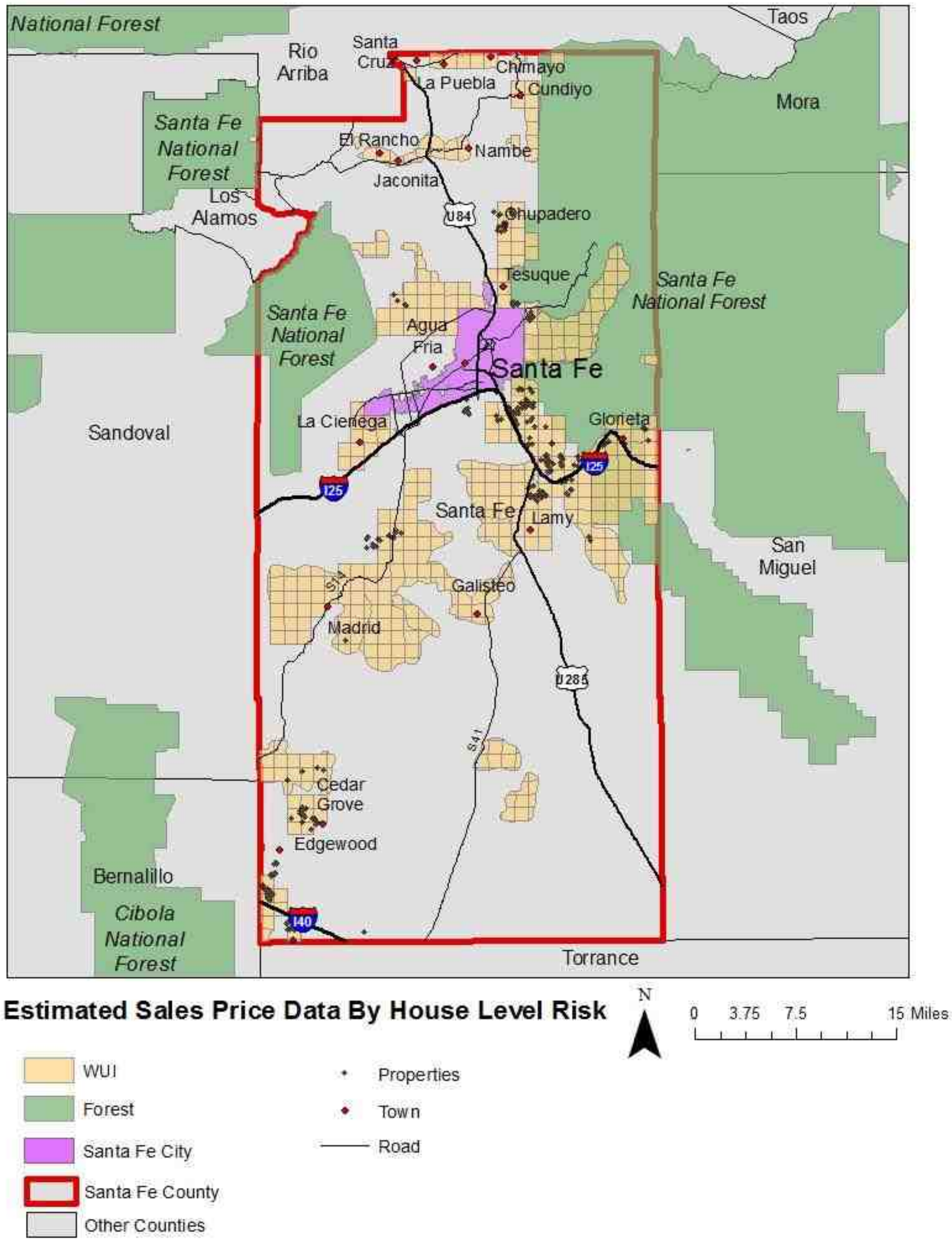
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.9: The distribution of single-family houses with regard to WUI risk in assessed value data



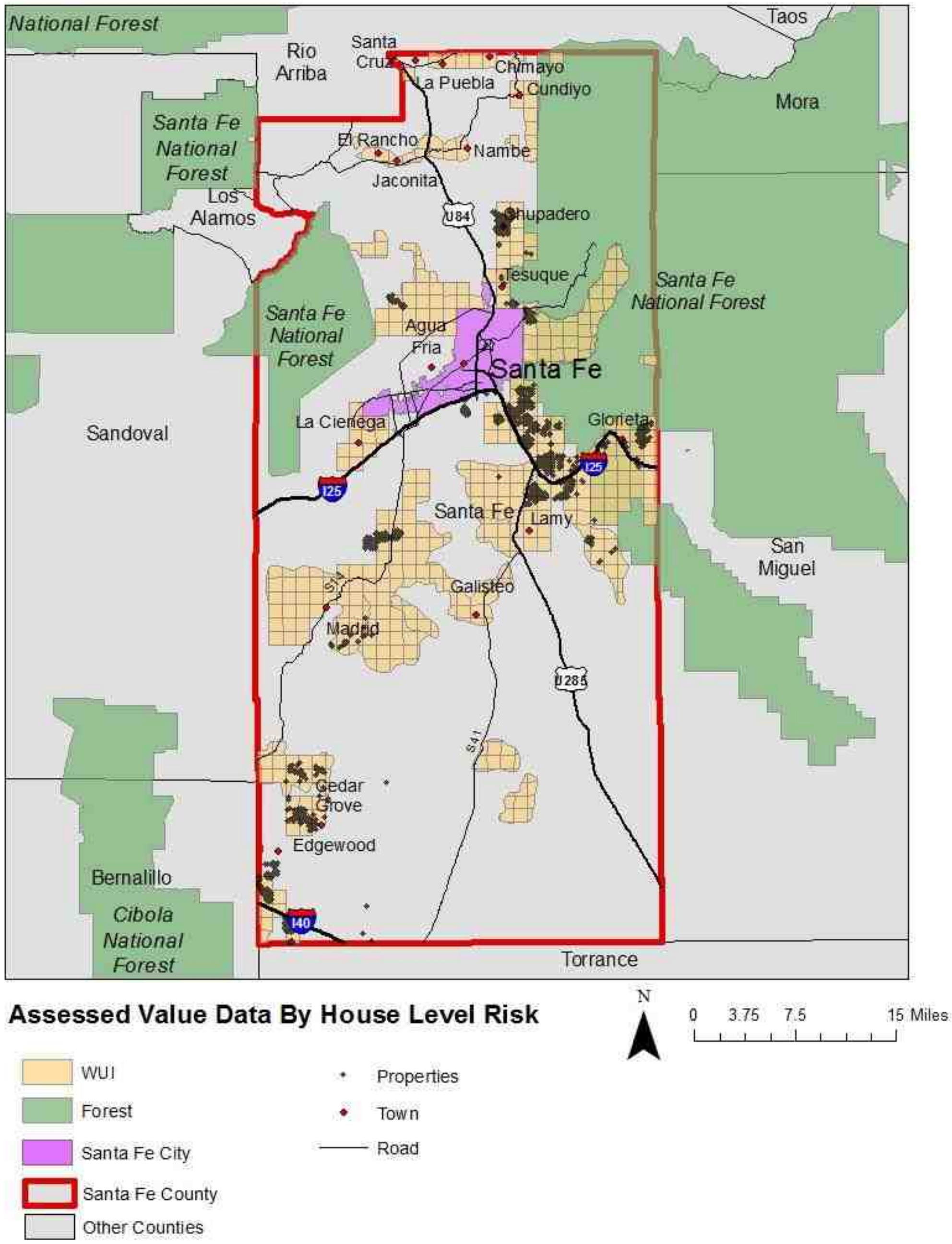
Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.10: The distribution of single-family houses with regard to individual-level house risk in estimated sales price data



Source: constructed by the author in ESRI ArcMap 10.1

Figure 5.11: The distribution of single-family houses with regard to individual-level house risk in assessed value data



Source: constructed by the author in ESRI ArcMap 10.1

Table 5.1: Three wildfire risk assessments

Wildfire Risk (WR) Assessment	Description	Source
GIS-based composite risk assessment	**Assessment 1** Fuels, topography and weather are inputs to fire behavior model (FARSITE, Behave Plus and Flammap), with outputs: flame length, rate of spread, fireline intensity, crown fire activity and spot fire potentials are predicted. These are combined with fire occurrence density, 1970 to 2007; Then, each output converted to values 1-4 (1= low, 2=medium, 3=high, 4=extreme). Outputs weighted to form composite risk assessment; weights for flame length, rate of spread, fireline intensity, crown fire activity and fire occurrence are 15%, 15%, 10%, 15% and 45%, respectively. Final assessment classifies the County into 4 risk categories: low, moderate, high and extreme.	Conducted by Santa Fe CWPP core team throughout Santa Fe County in 2007; Obtained from the Santa Fe GIS Division.
WUI risk assessment	**Assessment 2** The WFA Hazard assessment form used; 2 components: fire environment and defensibility. Fire environment considers fuel hazards, slope hazards and special hazards (e.g., drought, insect-killed trees); defensibility considers access, structure type, defensibility space and water availability; total possible points for fire environment and defensibility are 20 and 16, respectively. Using these scores, all 43 WUI areas were then classified into 4 risk categories: moderate, high, very high, and extreme risk.	Conducted by Santa Fe CWPP core team in WUI areas in 2007; Obtained from the Santa Fe GIS Division.
On-site, individual-level house risk assessment	**Assessment 3** 3 factors considered: site hazard, structural hazard, and hazard reduction factors. The total possible points for these 3 factors were 105, 45 and -15, respectively. These ratings were then combined with WUI risk assessment score to determine individual house's numerical risk score, which ranged from 24 to 188 (highest risk).	Conducted on-site by the Santa Fe Fire Wildland Division, 2009-2013; focus on WUI areas; Obtained from the Santa Fe Fire Wildland Division.

Table 5.2: Variable Descriptions in the hedonic model

Variable	**Description**
Dependent Variables	
Assval	Assessed value
Estsalep	Estimated sale prices (adjusted to 2013 dollars)
Structural Variables	
Area	Dwelling area (square feet)
Lotsize	Lot size (square feet)
Yrxxxx[a]	Dummy variables for year of sale from year 2004 to year 2013 (Omitted case is 2003)
Bedroom	Number of bedrooms
Bathroom	Number of bathrooms
Fireplace	Dummy variable equals 1 if a house has a fireplace, else 0
Aircond	Dummy variable equals 1 if a house has a central air system, 0 otherwise (Omitted case is none)
Evapcool	Dummy variable equals 1 if a house has evaporative system, 0 otherwise (Omitted case is none)
Othercool	Dummy variable equals 1 if a house forced cool air, package unit or window units, 0 otherwise (Omitted case is none)
Phycond	Physical condition (1=low, 2=fair, 3=average, 4=good, 5=very good, 6=excellent, 7= highly improved)
Neighborhood Variables	
Highsch	Percentage of residents aged 25 and older in census tract with high school degree and above
Over65	Percentage of the population over 65 years old in the census tract
White	Percentage of white population in census tract
Environmental Variables	
Highway	Distance to the nearest highway (kilometers)
City	Distance to the nearest town/city (kilometers)
Industry	Distance to the nearest area that is classified as industry (kilometers)
Lake	Distance to the nearest area that is classified as lake or reservoir
Forest	Distance to the nearest forest boundary (kilometers)
Wildfire Variables	
WUI	Dummy variable if a home is located in the WUI, else 0
1. Wildfire Event/occurrence	
(1) the nearest fire measure	
Dist	Distance between the nearest fire burned and the house (kilometers)
Timesincefire	Time since the nearest fire burned (month)
Size	Size of the nearest fire (acres)
(2) the aggregate fire measure	
Firenum_10	Number of fires within 10 km of the house
Firenum_15	Number of fires within 15 km of the house

Variable	Description
Firenum_20	Number of fires within 20 km of the house
Firenum_25	Number of fires within 25 km of the house
Avgsize_10	Average size of fires within 10 km of the house (acres)
Avgsize_15	Average size of fires within 15 km of the house (acres)
Avgsize_20	Average size of fires within 20 km of the house (acres)
Avgsize_25	Average size of fires within 25 km of the house (acres)
2. Wildfire Risk	
(1) Composite Risk	
Comp_high	Dummy variable equals 1 if composite risk level is high, else 0
Comp_ext	Dummy variable equals 1 if composite risk level is extreme, else 0
(2) WUI Risk	
WUI_high	Dummy variable equals 1 if WUI risk level is high, else 0
WUI_vhigh	Dummy variable equals 1 if WUI risk level is very high, else 0
WUI_ext	Dummy variable equals 1 if WUI risk level is extreme, else 0
(3) House risk	
Hriskscore	Individual house fire risk score

[a] xxxx after Yr indicate sale year. For example, Yr2004 equals one if a house was sold in 2004, and zero otherwise.

Table 5.3: Descriptive statistics (estimated sale prices data)

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Estsalep	10639	361370	247304	60938	4655000
Area	10639	1985	919.69	448	11837
Land	10639	61576	762191	929	77000000
Bedroom	10639	3.22	0.85	1	7
Bathroom	10639	2.04	0.84	1	11
Fireplace	10639	0.69	0.46	0	1
Aircond	10639	0.1	0.3	0	1
Evapcool	10639	0.14	0.35	0	1
Othercool	10639	0.16	0.37	0	1
Phycond	10639	3.8	1.02	1	7
Highsch	10639	0.9	0.09	0.57	0.99
Over65	10639	0.18	0.09	0.03	0.58
White	10639	0.87	0.06	0.52	0.99
Highway	10639	1.29	1.53	0	11.37
City	10639	0.5	1.23	0	16.46
Industry	10639	4.83	3.52	0.07	30.22
Lake	10639	9.04	4.89	0	27.11
Forest	10639	5.24	3.34	0	31.35
WUI	10639	0.24	0.43	0	1
Fires burned in the last 7 years (7-year time window)					
Dist	10639	19.24	6.66	0.98	41.01
Timesincefire	10639	57.58	28.14	2.04	92.48
Size	10639	4570.21	17465.2	9.88	156624.4
Firenum_10	10639	0.13	0.38	0	5
Firenum_15	10639	0.33	0.66	0	7
Firenum_20	10639	0.78	1.01	0	8
Firenum_25	10639	1.98	1.67	0	10
Avgsize_10	10639	68.15	969.55	0	42981.3
Avgsize_15	10639	334.2	2325.53	0	42981.3
Avgsize_20	10639	1258.64	4678.9	0	156624.4
Avgsize_25	10639	2858.7	8110.92	0	156624.4
Fires burned in the last 15 years (15-year time window)					
Dist	10639	10.88	4.34	0.25	35.5
Timesincefire	10639	124.47	40.48	2.07	187.43
Size	10639	638.53	5739.45	9.88	156624.4
Firenum_10	10639	0.52	0.67	0	7
Firenum_15	10639	1.22	0.89	0	10
Firenum_20	10639	2.22	1.26	0	12
Firenum_25	10639	4.38	2.35	0	18
Avgsize_10	10639	74.05	951.68	0	42981.3
Avgsize_15	10639	312.67	2529.44	0	42981.3
Avgsize_20	10639	729.29	2401.26	0	68632.8

Variable	N	Mean	Std. Dev.	Min	Max
Avgsize_25	10639	2390.64	4225.38	0	78659.54
Comp_high	10639	0.35	0.48	0	1
Comp_ext	10639	0.02	0.14	0	1
WUI_high	2529	0.6	0.49	0	1
WUI_vhigh	2529	0.05	0.22	0	1
WUI_ext	2529	0.02	0.15	0	1
Hriskscore	266	77.35	17.54	30	135
Yr2004	10639	0.09	0.29	0	1
Yr2005	10639	0.12	0.32	0	1
Yr2006	10639	0.12	0.33	0	1
Yr2007	10639	0.12	0.32	0	1
Yr2008	10639	0.08	0.28	0	1
Yr2009	10639	0.07	0.26	0	1
Yr2010	10639	0.07	0.25	0	1
Yr2011	10639	0.07	0.25	0	1
Yr2012	10639	0.08	0.28	0	1
Yr2013	10639	0.08	0.28	0	1

Table 5.4: Descriptive statistics (assessed value data)

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Assval	41004	314805	322353	17691	20400000
Area	41004	2134	1152	168	23336
Land	41004	127588	2915575	486	398000000
Bedroom	41004	3.25	1.04	1	8
Bathroom	41004	2.05	0.95	1	30
Fireplace	41004	0.67	0.47	0	1
Aircond	41004	0.07	0.26	0	1
Evapcool	41004	0.12	0.33	0	1
Othercool	41004	0.13	0.33	0	1
Phycond	41004	3.67	1.06	1	7
Highsch	41004	0.9	0.09	0.57	0.99
Over65	41004	0.19	0.09	0.03	0.58
White	41004	0.87	0.07	0.52	0.99
Highway	41004	1.24	1.54	0	11.51
City	41004	0.49	1.35	0	25.6
Industry	41004	5.36	4.02	0	42
Lake	41004	8.45	4.97	0	27.34
Forest	41004	5.16	3.95	0	31.35
WUI	41004	0.28	0.45	0	1
Fires burned in the last 7 years (7-year time window)					
Dist	41004	20.24	4.24	3.44	41.62
Timesincefire	41004	19.22	9.79	4.34	68.22
Size	41004	6271.64	13781.3	20.01	156624.4
Firenum_10	41004	0.01	0.12	0	2
Firenum_15	41004	0.09	0.31	0	2
Firenum_20	41004	0.54	0.56	0	3
Firenum_25	41004	1.76	0.95	0	7
Avgsize_10	41004	114.25	1068.44	0	10111.95
Avgsize_15	41004	721.48	2600.28	0	10111.95
Avgsize_20	41004	4328.48	13058.7	0	156625
Avgsize_25	41004	7778.04	15554.8	0	83368.5
Fires burned in the last 15 years (15-year time window)					
Dist	41004	13.54	4.22	0.91	36.12
Timesincefire	41004	152.73	49.45	8.78	177.37
Size	41004	1576.81	6435.98	9.88	42981.3
Firenum_10	41004	0.24	0.53	0	7
Firenum_15	41004	0.83	1.05	0	9
Firenum_20	41004	2.12	1.58	0	11
Firenum_25	41004	5.12	2.57	0	16
Avgsize_10	41004	227.05	1579.9	0	42981.47
Avgsize_15	41004	977.17	4192.82	0	42981.47
Avgsize_20	41004	2729.53	6610.46	0	99803.26

Variable	N	Mean	Std. Dev.	Min	Max
Avgsize_25	41004	4846.82	8230.3	0	52521.67
Comp_high	41004	0.31	0.46	0	1
Comp_ext	41004	0.02	0.16	0	1
WUI_high	11495	0.56	0.5	0	1
WUI_vhigh	11495	0.07	0.26	0	1
WUI_ext	11495	0.02	0.15	0	1
Hriskscore	1293	79.2	17.62	24	137

Table 5.5: Data and econometric modeling techniques

Variation		Categories	
Data	Data for housing prices	HP_AV	1. Assessed value
		HP_ESP	2. Estimated sale price
	Measures for past fire event/occurrence	*The nearest fire measure*	
		NEAR7	1. 7-yr time window
		NEAR15	2. 15-yr time window
		The aggregate fire measure	
		AGG710	3. 10km radius, 7-yr time window
		AGG715	4. 15km radius, 7-yr time window
		AGG720	5. 20km radius, 7-yr time window
		AGG725	6. 25km radius, 7-yr time window
		AGG1510	7. 10km radius, 15-yr time window
		AGG1515	8. 15km radius, 15-yr time window
		AGG1520	9. 20km radius, 15-yr time window
		AGG1525	10. 25km radius, 15-yr time window
	Wildfire risk measures (and geographic area)	COMP_CT	1. Composite risk covering Santa Fe County
		COMP_NWUI	2. Composite risk covering the Non-WUI area
		COMP_WUI	3. Composite risk covering the WUI area
		WUIRISK	4. WUI risk
		HRISK	5. House level risk
Econometric Modeling	Spatial model and spatial weights	OLS	1. No spatial OLS
		LAG_KNN4	2. Spatial lag model with KNN4 weight matrix
		LAG_KNN8	3. Spatial lag model with KNN8 weight matrix
		LAG_DIS0.5	4. Spatial lag model with the distance inverse weight matrix
		ERR_KNN4	5. Spatial error model with KNN4 weight matrix
		ERR_KNN8	6. Spatial error model with KNN8 weight matrix
		ERR_DIS0.5	7. Spatial error model with the distance inverse weight matrix
		GEN_KNN4	8. General spatial model with KNN4 weight matrix
		GEN_KNN8	9. General spatial model with KNN8 weight matrix
		GEN_DIS0.5	10. General spatial model with the distance inverse weight matrix
	Hedonic functional form	SEMILOG	1. Semi-log
		DOUBLELOG	2. Double-log

Chapter 6 Model specification testing and estimation results

In this chapter, I examine the presence of spatial correlation for all estimated models through 2 tests: Moran's I and LM test. Generally, Moran's I test show evidence for spatial correlation. I then selectively present the results of the preferred model.

6.1 Spatial model specification testing

I perform Moran's I and LM test to explore the spatial correlation for all samples. Table 6.1 to 6.3 report Moran's I statistics on OLS residuals for the assessed value models and the estimated sales price models, respectively. With regard to assessed value model, Moran's I statistics are significant, indicating the presence of spatial correlation in all cases. However, for the estimated sales price data, Moran's I statistics show evidence for spatial correlation with exception of models that use house level risk rating. That is, I failed to reject the null hypothesis of no spatial correlation for models that use the estimated sales price as the dependent variable and house-level risk rating as the independent variable.

One caveat with Moran's I statistics is that it doesn't point to the proper alternative (e.g., the spatial error model, the spatial lag model). LM test, including the simple LM and robust LM test, is then performed to further identify type of spatial correlation. LM test results are listed in Table 6.4-6.9. Table 6.4-6.6 report results for the assessed value data. One can see that all simple LM test results are statistically significant, and hence I strongly reject the null hypothesis of no spatial correlation in the error term as well as in the dependent variable. LM test statistics for estimated sales price data are reported in Table 6.7-6.9. The simple LM test statistic show both spatial correlated errors and spatial correlated lagged dependent variables, except for models that use house level risk rating, which are generally insignificant.

Table 6.10 summarizes LM test statistic results in Table 6.4-6.9. One can see that the preferred specification varies by the choice of data, geographic area, hedonic functional form and spatial weight matrix. Take the example of functional form, for models that use composite risk rating covering Santa Fe County area and knn4 weight matrix, the spatial lag model is preferred if semi-log functional form is used whereas the spatial error model is preferred if double-log functional form is used. The preferred specification is dependent on the data source for property value too. For models that use house level risk rating, generally I failed to reject the null hypothesis of no spatial correlation for estimated sales price data while spatial correlation is present for assessed value data. The preferred specification also varies across geographic area. For example, for models that use composite risk and knn8 weight matrix, spatial error model is appropriate if geographic area is the whole county or the Non-WUI area while spatial lag model is appropriate if study area is restricted to the WUI.

6.2 Examples of estimation results

For reasons of space, I selectively present results for the preferred hedonic models. First, I report results for models using assessed value as the dependent variable, the nearest fire measure with 7-year time window, double-log functional form with varying risk ratings (composite risk, WUI risk and house level risk rating). Then I illustrate results for models using estimated sales price as the dependent variable, the aggregate fire measure with 7-year time window, the semi-log functional form with various risk data.

I also include the MIP estimates in the tables. The MIP estimate is calculated using the average housing value and the average level of the independent variable for the sample population. For example, the average assessed value of single-family houses in Santa Fe County is $314,805 and the average sale price is $361,370. Calculation of the implicit price varies depending on variable type, functional form and econometric modelling techniques. For example, one needs to consider the spillover effect in SLM and GSM, and therefore the MIP estimate should be adjusted by the spatial lag coefficient ρ. The MIP estimates are directly comparable across OLS and SEM models. Calculation of the MIP is presented in Table 6.11. The percentage impact of dummy variables is calculated according to $100 * (e^{\widehat{\beta_D}} - 1)$ (Halvorsen and Palmquist, 1980).

6.2.1 Model 1: models using assessed data, the nearest fire measure with 7-year time window and double-log functional form

The estimated coefficients, standard error and MIP estimates of Model 1 are reported from Table 6.12 to Table 6.16. The overall fit of OLS model is pretty good, with adjusted R-squared ranging from 0.76 to 0.81.

First, let’s take a look at the estimated coefficients for Model 1 with composite risk rating covering Santa Fe County area. Column 1 of Table 6.12 reports OLS results. With respect to housing structural characteristics, almost all variables are of expected sign and highly significant. Square footage (*Area*), lot size (*Land*), number of bedrooms (*Bedroom*), number of bathrooms (*Bathroom*) and having a fireplace (*Fireplace*), are all significant and have positive effects on assessed value. House cooling system has mixed effects. Specifically, presence of central air system (*Aircond*), forced cool air, package unit and window units (*Othercool*) increase assessed value, compared to houses with no cooling system. Presence of evaporative system (*Evapcool*) has a negative and unexpected effect. Property physical condition (*Phycond*) have a positive effect, indicating that properties in better conditions have a higher value.

In terms of neighborhood characteristics, the percentage of residents have high school degree and above (*Highsch*) and the percentage of residents are 65 and older (*Over65*) in census tract are found to increase assessed property value in a statistically significant manner, which are in line with previous results in the hedonic literature. The estimated coefficient on the percentage of white population (*White*) is not statistically significant.

With respect to environmental attributes, proximity to the nearest highway (*Highway*) and the nearest town/city boundary (*City*) have positive effects on assessed value. However proximity to the industrial area (*Industry*) has a negative effect. These establishments measure accessibility to convenience, which tend to increase housing value. Nonetheless, they also generate dis-amenities such as crowd, traffic and noise, which are expected to have a negative impact. The estimated coefficients on the distance to lake (*Lake*) and the distance to forest boundary (*Forest*) are negative and significant, implying that houses far away from these environmental amenities have a lower assessed value, as one would expect.

Wildfires are found to have significant effect on assessed value. Generally, past wildfire event/occurrence has a negative effect on assessed value. The coefficient on the distance to the nearest fire (*Dist*) is positive and significant, revealing that assessed value increases as the distance from the nearest fire increases. The MIP for a one 1 km increase in the distance from nearest fire is $1,881 (in 2013 dollars), indicating an increase in assessed value of 0.6%. Nonetheless, the estimated coefficient on *Timesincefire* is significantly negative. Although unexpected, this result is not surprising since the actual sale date is not available for assessed value data and the time lag measures the lag between the time the nearest fire burned and the assessment year 2013. Assessed value decreases with the size of the fire (*Size*). This suggests that the bigger the fire the lower assessed value. Composite fire risk increases assessed value significantly; houses located in higher composite risk zones have a higher assessed value. Assessed value of properties located in the high and extreme composite risk zones are $13,311 and $31,082 higher than ones in the low or moderate risk zones, respectively. Accordingly, these values indicate 0.42% and 10% of assessed value. There is little difference in assessed value between houses located in the WUI (*WUI*) and ones located in the Non_WUI.

Table 6.12 also provides results of spatial error model for all three weight matrices. The sign and significance of all housing structure, neighborhood and environmental characteristics are very similar to OLS results. Lambda, the coefficient on the spatial correlated error variable, is statistically significant for all three weight matrices. This is consistent with Moran's I and LM test results. I note, however, the following changes. *Evapcool* variable is not statistically significant for all three weight matrices, indicating little difference exists in assessed values for properties that have evaporative system and ones that have no cooling system. The estimated coefficient on *City* becomes statistically negative for the inverse-distance weight matrix. The coefficients on high level composite risk (*Comp_high*) are still significantly positive whereas the coefficients on extreme composite risk level (*Comp_ext*) become insignificant for the knn8 and the inverse-distance weight matrices. Since both amenity and risk are confounded in risk rating, one possible explanation is that the negative effects of risk are more likely to offset the positive effects of amenity for areas with higher risks. Furthermore, in all three weight matrices, the estimated coefficient on WUI becomes significantly negative for the knn4 and knn8 weight matrices but significantly positive for the inverse-distance weight matrix. With respect to the magnitude of the effect, I see that the impacts of some wildfire variables become larger in the spatial autoregressive models (e.g., *WUI* and *Size*) while others become smaller (e.g., *Comp_high* and *Comp_ext*).

The effect of composite risk rating is expected to vary across geographic area. I further explore this issue by estimating separate models for houses located in the Non-WUI and the WUI area. Column 1 of Table 6.13 and Table 6.14 reports OLS results for the Non-WUI and the WUI models, respectively. Comparing OLS results in Table 6.12, Table 6.13 and Table 6.14, one can see that the estimated coefficients are very similar[15]. It is notable that the estimated coefficient on *Dist* becomes significantly negative in the Non-WUI model, which is contrary to the previous results and our expectation[16]. Comparing the coefficients on composite risk variables across the Non-WUI and the WUI model, results show that geographic area has a dramatic effect on the relationship

[15] In Non-WUI area model the exception is *White*, which becomes positively significant. In the WUI area model, *Highsch* and *White* have significant and unexpected negative effects; *Industry* becomes insignificant.

[16] However, the negative relationship between *Dist* and assessed value is not common, only found in 5% of models that use the assessed value data.

between composite risk and assessed value. High composite risk (*Comp_high*) and extreme risk (*Comp_ext*) are both positive and statistically significant in the Non-WUI model, which now become negative or insignificant in the WUI model, again consistent with our hypothesis. Since there are two conflating effects, amenity and risk, associated with the risk rating, homeowners in the Non-WUI have a preference for amenity while homeowners in the WUI are more concerned about fire risk. Thus the positive effects of amenity value outweigh the negative ones in the Non-WUI. However, these two effects cancel each other out or the negative effects of risk outweigh the positive effects in the WUI. Table 6.13 and 6.14 also provide the best fit spatial econometric models. Spatial model results remain very similar to OLS results. I also see similar pattern regarding the effect of composite risk rating in spatial autoregressive models across the Non-WUI and the WUI models.

Model 1 with WUI risk rating results are reported in Table 6.15. I begin by examining OLS results. The sign and significance of the coefficients are very similar to the previous results. The estimated coefficient on *Dist* is positively significant while the estimated coefficients on *Timesincefire* and *Size* are negatively significant. WUI risk has mixed effects. Compared to moderate level WUI risk, high level WUI risk (*WUI_high*) increases housing value, very high WUI risk level (*WUI_vhigh*) reduces housing value and there is little difference between the effect of moderate and extreme WUI risk (*WUI_ext*). This indicates that below certain risk level, wildfire risk increases house value; beyond that range the negative effects of risk offset, or even outweighs the positive effects of amenity, resulting in lower house value. One can see that assessed value are $35,251 higher for houses located in the high WUI risk zone whereas $43,845 lower for houses located in the very high WUI risk zone, as compared with moderate WUI risk properties. Furthermore, spatial model results are quite similar to OLS results.

Table 6.16 provides results for Model 1 with house level risk rating. First, house level risk rating (*Hriskscore*) has a negative effect on assessed value. That is, houses with higher risk rating would have a lower assessed value. This result is expected given that the assessment puts more weight on risk factors that contribute to high risk but not necessarily to high amenity value (e.g., location of firewood, debris, gas cans and gas grills), and these factors negatively affect property value. On average, the MIP for a one point increase in house risk score is $692 (in 2013 dollars). With respect to variables measuring the nearest fire, the variable *Dist* is still found to be positively significant. Assessed value still decrease with *Timesincefire*. However, the size of the fire (*Size*) now has a positive effect, suggesting that the bigger the fire the higher assessed value. This may be caused by the removal of a larger amount of flammable vegetation in areas previously afflicted by wildfire, which may reduce the perception of risk in those locations (Gardner et al., 1987). Spatial model results remain similar to OLS results.

6.2.2 Model 2: models using estimated sales price, the aggregate fire measure with 7-year time window and semi-log functional form

The estimated coefficients and standard errors are reported from Table 6.17 to Table 6.21. The MIP estimates are reported in Table 6.22 due to space limitations. Based on OLS results, adjusted R-squared of the various models are above 0.64, indicating good fit.

I are now turning to results for Model 2 with composite risk rating covering Santa Fe County. Table 6.17 reports OLS results for 10km, 15km, 20km and 25km buffer zones. Most variables, including housing structural characteristics, neighborhood and environmental characteristics, remain very similar to the previous results. There are several points to be seen regarding wildfire variables. First, houses located in the WUI have a higher estimated sales prices. Secondly, the estimated coefficients on the number of fires (*Firenum*) are generally negative and statistically significant (except for 25km buffer zone), indicating that average number has a negative effect on sale prices. Furthermore, this effect decay with the radius of the buffer zone; that is, the closer the wildfires, the greater effects on estimated sales prices. This result is consistent with findings in previous hedonic literature and our hypothesis. The MIP for an additional fire burned within 10km, 15k and 20k radius of a property, are $16,985, $12,287 and $12,287, respectively. All MIP estimates are measured in 2013 dollars. With respect to average size of fires (*Avgsize*), the effect is generally not significant. The estimated coefficients on composite risk are significantly positive.

Table 6.18 reports spatial error model results for the inverse-distance weight matrix. The sign and significance of the estimated coefficients are quite similar to OLS results in Table 6.17. The variable *Firenum* is still negative and statistically significant, and the magnitude of the coefficient decrease as the radius of buffer zone increase. Average size of fires have no significant effect. The estimated coefficient on *Comp_high* is still positive and significant while the estimated coefficient on *Comp_ext* becomes insignificant.

OLS results for Model 2 with WUI risk rating are presented in Table 6.19. The sign, significance and magnitude of the number of fires are still as expected. WUI risks were found to be statistically insignificant, expect for *WUI_vhigh* for 25k buffer zone.

Spatial error model results in Table 6.20 are very similar to OLS results. The key determinant of sale price continues to be the number of fires. Average size and WUI risks are not statistically significant.

Table 6.21 contains OLS model results for Model 2 with house level risk rating. Generally, the variables on wildfire are statistically insignificant. All other variables also become statistically insignificant except for house area, physical condition, the distance to water/lake and the distance to industrial area.

Table 6.1: Moran's I test results for the nearest fire measure

Wildfire risk data	**Weight matrix**	**Assessed value**		**Estimated sale price**	
		7-yr	**15-yr**	**7-yr**	**15-yr**
		SEMILOG			
Composite risk (county)	KNN4	0.28[a]	0.27[a]	0.13[a]	0.12[a]
	KNN8	0.27[a]	0.26[a]	0.12[a]	0.11[a]
	DIS0.5	0.2[a]	0.19[a]	0.1[a]	0.09[a]
Composite risk (Non-WUI)	KNN4	0.28[a]	0.27[a]	0.13[a]	0.12[a]
	KNN8	0.26[a]	0.26[a]	0.12[a]	0.11[a]
	DIS0.5	0.17[a]	0.16[a]	0.1[a]	0.08[a]
Composite risk (WUI)	KNN4	0.2[a]	0.21[a]	0.06[a]	0.05[a]
	KNN8	0.18[a]	0.19[a]	0.04[a]	0.04[a]
	DIS0.5	0.16[a]	0.16[a]	0.05[a]	0.05[a]
WUI risk	KNN4	0.19[a]	0.2[a]	0.06[a]	0.05[a]
	KNN8	0.17[a]	0.18[a]	0.04[a]	0.04[a]
	DIS0.5	0.15[a]	0.15[a]	0.05[a]	0.05[a]
House risk	KNN4	0.15[a]	0.13[a]	-0.01	-0.05
	KNN8	0.14[a]	0.13[a]	-0.01	-0.05
	DIS0.5	0.15[a]	0.12[a]	-0.03	-0.05
		DOUBLELOG			
Composite risk (county)	KNN4	0.29[a]	0.28[a]	0.13[a]	0.13[a]
	KNN8	0.28[a]	0.27[a]	0.12[a]	0.11[a]
	DIS0.5	0.21[a]	0.19[a]	0.1[a]	0.1[a]
Composite risk (Non-WUI)	KNN4	0.29[a]	0.28[a]	0.14[a]	0.13[a]
	KNN8	0.27[a]	0.26[a]	0.13[a]	0.12[a]
	DIS0.5	0.17[a]	0.17[a]	0.1[a]	0.09[a]
Composite risk (WUI)	KNN4	0.19[a]	0.19[a]	0.07[a]	0.07[a]
	KNN8	0.18[a]	0.17[a]	0.05[a]	0.05[a]
	DIS0.5	0.16[a]	0.15[a]	0.06[a]	0.07[a]
WUI risk	KNN4	0.17[a]	0.17[a]	0.07[a]	0.06[a]
	KNN8	0.16[a]	0.15[a]	0.05[a]	0.04[a]
	DIS0.5	0.14[a]	0.13[a]	0.06[a]	0.06[a]
House risk	KNN4	0.15[a]	0.13[a]	-0.02	-0.07
	KNN8	0.15[a]	0.13[a]	-0.01	-0.06
	DIS0.5	0.15[a]	0.13[a]	-0.04	-0.07

[a] significant at 1% level.

Table 6.2: Moran's I test results for the aggregate fire measure (Data = Assessed value)

Wildfire risk data	**Weight matrix**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
		SEMILOG							
Composite risk (county)	KNN4	0.295[a]	0.28[a]	0.296[a]	0.283[a]	0.288[a]	0.265[a]	0.268[a]	0.286[a]
	KNN8	0.278[a]	0.264[a]	0.28[a]	0.268[a]	0.272[a]	0.248[a]	0.252[a]	0.271[a]
	DIS0.5	0.212[a]	0.195[a]	0.213[a]	0.201[a]	0.205[a]	0.175[a]	0.181[a]	0.204[a]
Composite risk (Non-WUI)	KNN4	0.285[a]	0.278[a]	0.28[a]	0.274[a]	0.285[a]	0.277[a]	0.278[a]	0.276[a]
	KNN8	0.27[a]	0.263[a]	0.265[a]	0.259[a]	0.27[a]	0.262[a]	0.262[a]	0.261[a]
	DIS0.5	0.179[a]	0.172[a]	0.171[a]	0.169[a]	0.179[a]	0.169[a]	0.17[a]	0.171[a]
Composite risk (WUI)	KNN4	0.231[a]	0.218[a]	0.206[a]	0.222[a]	0.22[a]	0.199[a]	0.196[a]	0.23[a]
	KNN8	0.214[a]	0.201[a]	0.188[a]	0.205[a]	0.203[a]	0.179[a]	0.177[a]	0.214[a]
	DIS0.5	0.192[a]	0.176[a]	0.165[a]	0.183[a]	0.18[a]	0.154[a]	0.154[a]	0.192[a]
WUI risk	KNN4	0.217[a]	0.213[a]	0.204[a]	0.213[a]	0.207[a]	0.196[a]	0.191[a]	0.216[a]
	KNN8	0.198[a]	0.196[a]	0.186[a]	0.195[a]	0.189[a]	0.177[a]	0.172[a]	0.199[a]
	DIS0.5	0.174[a]	0.171[a]	0.162[a]	0.171[a]	0.164[a]	0.152[a]	0.149[a]	0.174[a]
House risk	KNN4	0.191[a]	0.171[a]	0.187[a]	0.193[a]	0.183[a]	0.178[a]	0.182[a]	0.201[a]
	KNN8	0.191[a]	0.17[a]	0.186[a]	0.193[a]	0.184[a]	0.179[a]	0.183[a]	0.202[a]
	DIS0.5	0.193[a]	0.172[a]	0.185[a]	0.195[a]	0.186[a]	0.179[a]	0.182[a]	0.203[a]
		DOUBLELOG							
Composite risk (county)	KNN4	0.307[a]	0.293[a]	0.307[a]	0.296[a]	0.301[a]	0.279[a]	0.281[a]	0.298[a]
	KNN8	0.291[a]	0.278[a]	0.292[a]	0.28[a]	0.286[a]	0.263[a]	0.265[a]	0.283[a]
	DIS0.5	0.224[a]	0.209[a]	0.224[a]	0.212[a]	0.217[a]	0.188[a]	0.193[a]	0.216[a]
Composite risk (Non-WUI)	KNN4	0.294[a]	0.289[a]	0.288[a]	0.284[a]	0.293[a]	0.289[a]	0.287[a]	0.286[a]
	KNN8	0.279[a]	0.273[a]	0.273[a]	0.269[a]	0.278[a]	0.274[a]	0.272[a]	0.271[a]
	DIS0.5	0.187[a]	0.181[a]	0.178[a]	0.176[a]	0.186[a]	0.178[a]	0.178[a]	0.179[a]
Composite risk (WUI)	KNN4	0.216[a]	0.208[a]	0.195[a]	0.21[a]	0.205[a]	0.189[a]	0.183[a]	0.218[a]
	KNN8	0.203[a]	0.195[a]	0.181[a]	0.197[a]	0.191[a]	0.175[a]	0.169[a]	0.205[a]
	DIS0.5	0.186[a]	0.178[a]	0.163[a]	0.18[a]	0.174[a]	0.156[a]	0.151[a]	0.188[a]
WUI risk	KNN4	0.2[a]	0.202[a]	0.192[a]	0.199[a]	0.192[a]	0.184[a]	0.174[a]	0.203[a]
	KNN8	0.186[a]	0.189[a]	0.179[a]	0.186[a]	0.178[a]	0.169[a]	0.16[a]	0.19[a]
	DIS0.5	0.168[a]	0.17[a]	0.16[a]	0.168[a]	0.16[a]	0.151[a]	0.142[a]	0.171[a]
House risk	KNN4	0.193[a]	0.175[a]	0.181[a]	0.19[a]	0.177[a]	0.176[a]	0.174[a]	0.203[a]
	KNN8	0.191[a]	0.173[a]	0.178[a]	0.188[a]	0.176[a]	0.178[a]	0.173[a]	0.202[a]
	DIS0.5	0.191[a]	0.174[a]	0.175[a]	0.188[a]	0.177[a]	0.176[a]	0.17[a]	0.202[a]

[a] significant at 1% level.

Table 6.3: Moran's I test results for the aggregate fire measure (Data = Estimated sale prices)

Wildfire risk data	**Weight Matrix**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
		SEMILOG							
Composite risk (county)	KNN4	0.126^{a}	0.122^{a}	0.119^{a}	0.127^{a}	0.127^{a}	0.124^{a}	0.117^{a}	0.126^{a}
	KNN8	0.116^{a}	0.111^{a}	0.109^{a}	0.117^{a}	0.117^{a}	0.113^{a}	0.106^{a}	0.115^{a}
	DIS0.5	0.096^{a}	0.093^{a}	0.09^{a}	0.098^{a}	0.098^{a}	0.094^{a}	0.088^{a}	0.096^{a}
Composite risk (Non-WUI)	KNN4	0.132^{a}	0.131^{a}	0.13^{a}	0.132^{a}	0.131^{a}	0.13^{a}	0.126^{a}	0.13^{a}
	KNN8	0.125^{a}	0.124^{a}	0.122^{a}	0.124^{a}	0.124^{a}	0.123^{a}	0.118^{a}	0.122^{a}
	DIS0.5	0.096^{a}	0.095^{a}	0.093^{a}	0.096^{a}	0.096^{a}	0.094^{a}	0.09^{a}	0.093^{a}
Composite risk (WUI)	KNN4	0.06^{a}	0.055^{a}	0.056^{a}	0.065^{a}	0.063^{a}	0.055^{a}	0.057^{a}	0.066^{a}
	KNN8	0.043^{a}	0.039^{a}	0.041^{a}	0.051^{a}	0.048^{a}	0.039^{a}	0.042^{a}	0.051^{a}
	DIS0.5	0.058^{a}	0.055^{a}	0.055^{a}	0.064^{a}	0.061^{a}	0.056^{a}	0.057^{a}	0.064^{a}
WUI risk	KNN4	0.057^{a}	0.054^{a}	0.055^{a}	0.061^{a}	0.059^{a}	0.053^{a}	0.055^{a}	0.062^{a}
	KNN8	0.04^{a}	0.039^{a}	0.039^{a}	0.046^{a}	0.043^{a}	0.038^{a}	0.039^{a}	0.047^{a}
	DIS0.5	0.055^{a}	0.054^{a}	0.053^{a}	0.06^{a}	0.057^{a}	0.055^{a}	0.054^{a}	0.06^{a}
House risk	KNN4	0.015^{c}	-0.031	0.009^{c}	0.035^{b}	0.021^{b}	-0.027	-0.025	0.012^{c}
	KNN8	0.011^{b}	-0.029	0.003^{c}	0.028^{a}	0.023^{a}	-0.036	-0.032	0.001^{c}
	DIS0.5	0.009	-0.028	-0.007	0.01	0.014^{c}	-0.017	-0.03	-0.004
		DOUBLELOG							
Composite risk (county)	KNN4	0.133^{a}	0.128^{a}	0.125^{a}	0.134^{a}	0.134^{a}	0.129^{a}	0.123^{a}	0.132^{a}
	KNN8	0.121^{a}	0.116^{a}	0.113^{a}	0.122^{a}	0.122^{a}	0.117^{a}	0.111^{a}	0.12^{a}
	DIS0.5	0.105^{a}	0.101^{a}	0.098^{a}	0.106^{a}	0.107^{a}	0.102^{a}	0.096^{a}	0.104^{a}
Composite risk (Non-WUI)	KNN4	0.137^{a}	0.136^{a}	0.134^{a}	0.136^{a}	0.135^{a}	0.135^{a}	0.129^{a}	0.134^{a}
	KNN8	0.13^{a}	0.128^{a}	0.126^{a}	0.129^{a}	0.128^{a}	0.127^{a}	0.121^{a}	0.126^{a}
	DIS0.5	0.103^{a}	0.102^{a}	0.099^{a}	0.103^{a}	0.102^{a}	0.101^{a}	0.096^{a}	0.1^{a}
Composite risk (WUI)	KNN4	0.071^{a}	0.069^{a}	0.069^{a}	0.077^{a}	0.076^{a}	0.068^{a}	0.071^{a}	0.077^{a}
	KNN8	0.049^{a}	0.048^{a}	0.048^{a}	0.057^{a}	0.055^{a}	0.048^{a}	0.05^{a}	0.058^{a}
	DIS0.5	0.07^{a}	0.069^{a}	0.068^{a}	0.075^{a}	0.074^{a}	0.069^{a}	0.07^{a}	0.075^{a}
WUI risk	KNN4	0.07^{a}	0.069^{a}	0.067^{a}	0.074^{a}	0.072^{a}	0.067^{a}	0.068^{a}	0.074^{a}
	KNN8	0.047^{a}	0.048^{a}	0.046^{a}	0.054^{a}	0.05^{a}	0.046^{a}	0.047^{a}	0.054^{a}
	DIS0.5	0.068^{a}	0.068^{a}	0.066^{a}	0.072^{a}	0.07^{a}	0.068^{a}	0.067^{a}	0.072^{a}
House risk	KNN4	0.007^{c}	-0.04	0.008^{c}	0.032^{b}	0.013^{c}	-0.033	-0.016	0.008^{c}
	KNN8	0.011^{b}	-0.032	0.006^{b}	0.034^{a}	0.02^{a}	-0.035	-0.021	0.007^{b}
	DIS0.5	0.005	-0.035	-0.008	0.012	0.01	-0.023	-0.024	-0.004

^{a} significant at 1% level.
^{b} significant at 5% level.
^{c} significant at 10% level.

Table 6.4: LM test results for the nearest fire measure (Data = Assessed value)

Wildfire risk data	**LM test**	**Past fire event/occurrence**			
		7-yr	**15-yr**	**7-yr**	**15-yr**
		SEMILOG		**DOUBLELOG**	
Composite risk (county)	Spatial weight matrix = KNN4				
	Error	7149.7[a]	6829.7[a]	7730.4[a]	7200.6[a]
	Lag	7709.8[a]	7152[a]	7077.9[a]	6044.5[a]
	RError	1208.8[a]	1225.8[a]	1793.3[a]	1909.1[a]
	RLag	1768.9[a]	1548.1[a]	1140.9[a]	753[a]
	Spatial weight matrix = KNN8				
	Error	12595.5[a]	11940.6[a]	13719.5[a]	12705.4[a]
	Lag	10029.3[a]	9215.6[a]	9269.5[a]	7821.4[a]
	RError	4499.5[a]	4401.1[a]	5703.1[a]	5685.5[a]
	RLag	1933.4[a]	1676.1[a]	1253.1[a]	801.4[a]
	Spatial weight matrix = DIS0.5				
	Error	39897.7[a]	35622.4[a]	43769.8[a]	37062.2[a]
	Lag	1496.1[a]	1386.2[a]	1292[a]	1207.1[a]
	RError	38670.6[a]	34509.2[a]	42669.5[a]	36076.6[a]
	RLag	269[a]	273[a]	191.6[a]	221.5[a]
Composite risk (Non-WUI)	Spatial weight matrix = KNN4				
	Error	4933.8[a]	4777.1[a]	5333.4[a]	5045.9[a]
	Lag	4818.6[a]	4687.9[a]	4508.9[a]	4291.2[a]
	RError	902.6[a]	879.6[a]	1258.2[a]	1199.3[a]
	RLag	787.4[a]	790.4[a]	433.7[a]	444.5[a]
	Spatial weight matrix = KNN8				
	Error	8761[a]	8442.7[a]	9492.2[a]	8962.1[a]
	Lag	6547.4[a]	6314.3[a]	6265.8[a]	5893.8[a]
	RError	3120.5[a]	3038.9[a]	3749.1[a]	3600.7[a]
	RLag	906.8[a]	910.4[a]	522.7[a]	532.4[a]
	Spatial weight matrix = DIS0.5				
	Error	30016.6[a]	27899.2[a]	32979.8[a]	29647.5[a]
	Lag	622.9[a]	658.9[a]	540.5[a]	591[a]
	RError	29480.4[a]	27356.5[a]	32498.4[a]	29151[a]
	RLag	86.7[a]	116.1[a]	59.2[a]	94.5[a]
Composite risk (WUI)	Spatial weight matrix = KNN4				
	Error	1008[a]	1105.6[a]	913[a]	886.4[a]
	Lag	1702[a]	1554.5[a]	1376.9[a]	1035.5[a]
	RError	53.7[a]	93.5[a]	95.1[a]	148.5[a]
	RLag	747.7[a]	542.5[a]	558.9[a]	297.6[a]
	Spatial weight matrix = KNN8				
	Error	1643[a]	1786.4[a]	1549.4[a]	1474.4[a]
	Lag	2030.8[a]	1862.3[a]	1636[a]	1201.8[a]
	RError	368.9[a]	458.5[a]	471.4[a]	543.3[a]
	RLag	756.6[a]	534.3[a]	558[a]	270.7[a]

Table 6.4: LM test results for the nearest fire measure (Data = Assessed value) (cont'd)

Wildfire risk data	**LM test**	**Past fire event/occurrence**			
		7-yr	**15-yr**	**7-yr**	**15-yr**
		SEMILOG		**DOUBLELOG**	
	Spatial weight matrix = DIS0.5				
	Error	3585.6[a]	3792.8[a]	3553.3[a]	3336.7[a]
	Lag	407.5[a]	326[a]	342.1[a]	218.6[a]
	RError	3322.1[a]	3557.9[a]	3332.1[a]	3175[a]
	RLag	144[a]	91.1[a]	120.9[a]	56.9[a]
WUI risk	Spatial weight matrix = KNN4				
	Error	943.7[a]	1002.9[a]	778.6[a]	723[a]
	Lag	1658.8[a]	1512.7[a]	1282[a]	919.8[a]
	RError	40.9[a]	66.9[a]	62.4[a]	102.1[a]
	RLag	755.9[a]	576.7[a]	565.8[a]	299[a]
	Spatial weight matrix = KNN8				
	Error	1513.7[a]	1590.4[a]	1291.3[a]	1163.6[a]
	Lag	1978.4[a]	1805.3[a]	1514.2[a]	1044.9[a]
	RError	309.3[a]	363.7[a]	348.8[a]	393.3[a]
	RLag	774[a]	578.7[a]	571.7[a]	274.6[a]
	Spatial weight matrix = DIS0.5				
	Error	3234.6[a]	3278.4[a]	2891.5[a]	2522.5[a]
	Lag	387.6[a]	318.5[a]	310.7[a]	201.9[a]
	RError	2989.5[a]	3059.7[a]	2699.9[a]	2384.6[a]
	RLag	142.5[a]	99.8[a]	119.2[a]	63.9[a]
House risk	Spatial weight matrix = KNN4				
	Error	62.6[a]	49.2[a]	69.3[a]	51.9[a]
	Lag	130.1[a]	93.9[a]	109.8[a]	81.4[a]
	RError	0.8	0.7	5.8[b]	3.7*
	RLag	68.3[a]	45.4[a]	46.4[a]	33.3[a]
	Spatial weight matrix = KNN8				
	Error	121.3[a]	96.2[a]	133.5[a]	105.9[a]
	Lag	195.6[a]	145.5[a]	164.2[a]	128.2[a]
	RError	16.1[a]	11.8[a]	32.1[a]	23.9[a]
	RLag	90.4[a]	61.1[a]	62.8[a]	46.2[a]
	Spatial weight matrix = DIS0.5				
	Error	145.8[a]	105.9[a]	158.4[a]	113.3[a]
	Lag	14.3[a]	11.8[a]	12.1[a]	7.6[a]
	RError	137.3[a]	99.4[a]	150.8[a]	108.4[a]
	RLag	5.9[b]	5.4[b]	4.5[b]	2.7

[a] significant at 1% level.
[b] significant at 5% level.

Table 6.5: LM test results for the aggregate fire measure (Data = Assessed value, Functional form = Semi-log)

Wildfire risk data	LM	Past fire event/occurrence							
		7-yr time window				15-yr time window			
		10km	15km	20km	25km	10km	15km	20km	25km
Composite risk (County)	Spatial weight matrix = KNN4								
	Error	7857.1[a]	7108.8[a]	7930.5[a]	7275.3[a]	7538.2[a]	6374.6[a]	6513.1[a]	7420.8[a]
	Lag	7878.1[a]	7575.3[a]	8042[a]	7842.8[a]	7692.7[a]	6721.2[a]	7146.9[a]	7981.7[a]
	RErro	1540.4[a]	1228.9[a]	1516.8[a]	1247[a]	1436.3[a]	1138.6[a]	1090.3[a]	1272.3[a]
	RLag	1561.4[a]	1695.5[a]	1628.3[a]	1814.5[a]	1590.9[a]	1485.2[a]	1724.2[a]	1833.2[a]
	Spatial weight matrix = KNN8								
	Error	13889.1[a]	12486[a]	14085[a]	12836.7[a]	13278.5[a]	11037.9[a]	11350.7[a]	13136.9[a]
	Lag	10197.8[a]	9808[a]	10479.4[a]	10188.5[a]	9917.4[a]	8522.6[a]	9166.8[a]	10417.7[a]
	RErro	5372.9[a]	4517.4[a]	5370.4[a]	4637.6[a]	5071.7[a]	4086.1[a]	4064.6[a]	4736.5[a]
	RLag	1681.6[a]	1839.4[a]	1764.8[a]	1989.4[a]	1710.5[a]	1570.7[a]	1880.7[a]	2017.2[a]
	Spatial weight matrix = DIS0.5								
	Error	46228.2[a]	39326.6[a]	46939[a]	41513.5[a]	43248.9[a]	31692[a]	33912.6[a]	43135.1[a]
	Lag	1570.1[a]	1473.8[a]	1618.3[a]	1606.5[a]	1541.6[a]	1149.5[a]	1499[a]	1709.6[a]
	RErro	44903.6[a]	38123[a]	45577.2[a]	40213.6[a]	41969.6[a]	30751.1[a]	32760.8[a]	41758.6[a]
	RLag	245.5[a]	270.1[a]	256.5[a]	306.6[a]	262.3[a]	208.6[a]	347.2[a]	333[a]
Composite risk (Non-WUI)	Spatial weight matrix = KNN4								
	Error	5271.2[a]	5002[a]	5089.6[a]	4869.6[a]	5263.7[a]	4986.9[a]	4998.5[a]	4939.5[a]
	Lag	5064.1[a]	5158[a]	4818.9[a]	4954.2[a]	5033.8[a]	4941.7[a]	4931[a]	5032.7[a]
	RErro	1020[a]	824[a]	1001.5[a]	842[a]	1019.7[a]	907.4[a]	916.5[a]	846.8[a]
	RLag	812.9[a]	980[a]	730.8[a]	926.6[a]	789.8[a]	862.2[a]	849.1[a]	940[a]
	Spatial weight matrix = KNN8								
	Error	9387.7[a]	8887.8[a]	9025.3[a]	8636.9[a]	9378[a]	8874.5[a]	8877.2[a]	8767.8[a]
	Lag	6824[a]	7016.3[a]	6475.2[a]	6694.9[a]	6801.4[a]	6662.2[a]	6656[a]	6827.4[a]
	RErro	3492.6[a]	3013.6[a]	3377.1[a]	3019.4[a]	3478.4[a]	3199.6[a]	3200.1[a]	3038.5[a]
	RLag	928.9[a]	1142[a]	827[a]	1077.4[a]	901.8[a]	987.3[a]	978.9[a]	1098.1[a]
	Spatial weight matrix = DIS0.5								
	Error	34529.1[a]	31754.2[a]	31607.9[a]	30705.1[a]	34385.9[a]	30907.7[a]	31137.7[a]	31634.4[a]
	Lag	741.7[a]	763.9[a]	657.2[a]	744.2[a]	712.8[a]	687.2[a]	740.8[a]	773.9[a]
	RErro	33898[a]	31125[a]	31044.7[a]	30096[a]	33772.5[a]	30329.9[a]	30526.6[a]	31001.3[a]
	RLag	110.6[a]	134.7[a]	94[a]	135[a]	99.3[a]	109.4[a]	129.6[a]	140.8[a]
Composite risk (WUI)	Spatial weight matrix = KNN4								
	Error	1370.4[a]	1219.3[a]	1089.7[a]	1260.6[a]	1246.9[a]	1017.4[a]	987.9[a]	1354.9[a]
	Lag	1980.1[a]	1823.4[a]	1766.4[a]	1949.9[a]	1805[a]	1503.5[a]	1580.5[a]	2014.5[a]
	RErro	124.6[a]	100.3[a]	68.9[a]	92.5[a]	110.1[a]	81.4[a]	62.9[a]	112.5[a]
	RLag	734.3[a]	704.4[a]	745.6[a]	781.8[a]	668.3[a]	567.5[a]	655.5[a]	772.1[a]
	Spatial weight matrix = KNN8								
	Error	2316.1[a]	2034.9[a]	1792.1[a]	2123.6[a]	2072.2[a]	1627.5[a]	1589.4[a]	2311.1[a]
	Lag	2430.1[a]	2205.1[a]	2128.3[a]	2396.3[a]	2179.6[a]	1752.2[a]	1871.6[a]	2493.8[a]
	RErro	637.4[a]	540.4[a]	427[a]	535.6[a]	561.4[a]	420.9[a]	375.9[a]	613.9[a]
	RLag	751.3[a]	710.6[a]	763.2[a]	808.3[a]	668.8[a]	545.6[a]	658.1[a]	796.6[a]
	Spatial weight matrix = DIS0.5								
	Error	5180.6[a]	4379[a]	3831.5[a]	4695.4[a]	4556.9[a]	3352[a]	3329.4[a]	5167.1[a]
	Lag	508.5[a]	456.1[a]	435.4[a]	484.8[a]	446.1[a]	334.2[a]	386.6[a]	519.6[a]
	RErro	4829.3[a]	4072.7[a]	3549.6[a]	4367.3[a]	4250.2[a]	3125.7[a]	3083.2[a]	4811.1[a]
	RLag	157.2[a]	149.7[a]	153.5[a]	156.7[a]	139.3[a]	107.9[a]	140.3[a]	163.7[a]

Table 6.5: LM test results for the aggregate fire measure (Data = Assessed value, Functional form = Semi-log) (cont'd)

Wildfire risk data	**LM**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
WUI risk	Spatial weight matrix = KNN4								
	Error	1204.3[a]	1169[a]	1067.6[a]	1164.3[a]	1105.5[a]	991.9[a]	938.9[a]	1200.1[a]
	Lag	1871.2[a]	1812.8[a]	1747.6[a]	1874.6[a]	1705.5[a]	1525.8[a]	1582.4[a]	1899.9[a]
	RError	85.5[a]	83.8[a]	63.4[a]	72.8[a]	78.6[a]	68.6[a]	48.2[a]	79.6[a]
	RLag	752.5[a]	727.6[a]	743.4[a]	783.1[a]	678.6[a]	602.5[a]	691.7[a]	779.4[a]
	Spatial weight matrix = KNN8								
	Error	1983.6[a]	1932.7[a]	1743.4[a]	1928[a]	1795.8[a]	1579.4[a]	1497[a]	1994.6[a]
	Lag	2285.5[a]	2203[a]	2109.1[a]	2296.1[a]	2048.7[a]	1790.9[a]	1879.5[a]	2335.4[a]
	RError	482[a]	476.7[a]	399.9[a]	449[a]	437[a]	379.4[a]	322.2[a]	474.1[a]
	RLag	783.8[a]	746.9[a]	765.7[a]	817[a]	689.8[a]	590.9[a]	704.7[a]	814.9[a]
	Spatial weight matrix = DIS0.5								
	Error	4252.6[a]	4091.7[a]	3681.7[a]	4134.4[a]	3787.9[a]	3235.7[a]	3103.3[a]	4279.7[a]
	Lag	475.8[a]	451.5[a]	427.3[a]	462.2[a]	418.5[a]	341.9[a]	388.2[a]	482[a]
	RError	3941.2[a]	3795.3[a]	3407.4[a]	3832[a]	3514.3[a]	3009.1[a]	2863.4[a]	3965[a]
	RLag	164.5[a]	155.1[a]	153.1[a]	159.8[a]	144.9[a]	115.3[a]	148.3[a]	167.4[a]
House risk	Spatial weight matrix = KNN4								
	Error	107.9[a]	85.8[a]	103.3[a]	109.4[a]	98.5[a]	93.3[a]	97.4[a]	119.4[a]
	Lag	201.2[a]	162.4[a]	180.6[a]	199.7[a]	180.7[a]	168.8[a]	166.8[a]	203.3[a]
	RError	3.6[c]	2.5	4[b]	3.8[c]	3.3[c]	3.3[c]	4[b]	5.7[b]
	RLag	96.9[a]	79.1[a]	81.2[a]	94.2[a]	85.4[a]	78.8[a]	73.3[a]	89.7[a]
	Spatial weight matrix = KNN8								
	Error	212.6[a]	167.3[a]	201.3[a]	217.3[a]	196[a]	187.4[a]	195.9[a]	237.4[a]
	Lag	298.7[a]	241.2[a]	272.6[a]	304.4[a]	272.8[a]	256.8[a]	255.5[a]	308.9[a]
	RError	38.4[a]	28.6[a]	35.7[a]	37.8[a]	34.8[a]	33.6[a]	36.1[a]	46.1[a]
	RLag	124.5[a]	102.5[a]	107[a]	124.9[a]	111.6[a]	103[a]	95.7[a]	117.6[a]
	Spatial weight matrix = DIS0.5								
	Error	253.6[a]	201.7[a]	233.2[a]	258.9[a]	236.1[a]	218.6[a]	225.3[a]	279.8[a]
	Lag	25.7[a]	23.1[a]	23[a]	26[a]	23.7[a]	24.1[a]	22.9[a]	25.7[a]
	RError	238.4[a]	188.9[a]	219.5[a]	243.5[a]	222.1[a]	205[a]	211.9[a]	264[a]
	RLag	10.5[a]	10.3[a]	9.3[a]	10.6[a]	9.7[a]	10.5[a]	9.5[a]	9.8[a]

[a] significant at 1% level.
[b] significant at 5% level.
[c] significant at 10% level.

Table 6.6: LM test results for the aggregate fire measure (Data = Assessed value, Functional form = Double-log)

Wildfire risk data	**LM**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
Composite risk (County)	Spatial weight matrix = KNN4								
	Error	8512[a]	7799.8[a]	8561.6[a]	7911.5[a]	8218.9[a]	7061.8[a]	7152.8[a]	8069.7[a]
	Lag	7506.4[a]	7113.9[a]	7625.7[a]	7322[a]	7227.6[a]	6020.6[a]	6581.7[a]	7489.3[a]
	RErro	2093.6[a]	1819.9[a]	2069.1[a]	1816.3[a]	2039.7[a]	1840.6[a]	1671.7[a]	1840[a]
	RLag	1088[a]	1134.1[a]	1133.2[a]	1226.7[a]	1048.5[a]	799.4[a]	1100.6[a]	1259.6[a]
	Spatial weight matrix = KNN8								
	Error	15178.8[a]	13836.3[a]	15311.6[a]	14070.2[a]	14615.9[a]	12371.6[a]	12604.4[a]	14398.7[a]
	Lag	9828.9[a]	9285.7[a]	10032.5[a]	9594.3[a]	9415.7[a]	7693.8[a]	8515.5[a]	9861[a]
	RErro	6530.9[a]	5784.5[a]	6516.4[a]	5833.1[a]	6331.6[a]	5511.8[a]	5293.8[a]	5938[a]
	RLag	1181.1[a]	1234[a]	1237.4[a]	1357.2[a]	1131.4[a]	834[a]	1204.9[a]	1400.3[a]
	Spatial weight matrix = DIS0.5								
	Error	51608.2[a]	44870.7[a]	51999[a]	46252.8[a]	48607.3[a]	36361.7[a]	38390.1[a]	48118.9[a]
	Lag	1423.6[a]	1345[a]	1451[a]	1459.1[a]	1397[a]	1020.7[a]	1379.4[a]	1575.7[a]
	RErro	50370.1[a]	43731.8[a]	50739.2[a]	45035.7[a]	47409.5[a]	35489.9[a]	37294.5[a]	46815[a]
	RLag	185.5[a]	206.1[a]	191.3[a]	242[a]	199.2[a]	148.9[a]	283.9[a]	271.8[a]
Composite risk (non-WUI)	Spatial weight matrix = KNN4								
	Error	5619.6[a]	5409.8[a]	5394.5[a]	5235.3[a]	5583.1[a]	5428.8[a]	5359.8[a]	5325.9[a]
	Lag	4892.6[a]	4928[a]	4589.6[a]	4595.3[a]	4847.1[a]	4640.4[a]	4664.2[a]	4691.3[a]
	RErro	1278.6[a]	1127.9[a]	1269.7[a]	1188.4[a]	1271.7[a]	1280.8[a]	1223.3[a]	1200.7[a]
	RLag	551.5[a]	646.1[a]	464.9[a]	548.4[a]	535.8[a]	492.4[a]	527.7[a]	566[a]
	Spatial weight matrix = KNN8								
	Error	10025[a]	9635.7[a]	9581.1[a]	9295[a]	9963.9[a]	9675.6[a]	9539.5[a]	9467.6[a]
	Lag	6738[a]	6828.1[a]	6297.1[a]	6317.4[a]	6686.8[a]	6382[a]	6424.9[a]	6464.1[a]
	RErro	3943.9[a]	3589.6[a]	3831.1[a]	3645.8[a]	3913.8[a]	3882.4[a]	3749[a]	3694.6[a]
	RLag	656.9[a]	782[a]	547.1[a]	668.2[a]	636.7[a]	588.9[a]	634.4[a]	691.2[a]
	Spatial weight matrix = DIS0.5								
	Error	37722.9[a]	35423.1[a]	34116.1[a]	33322.6[a]	37286[a]	34328.2[a]	34100.2[a]	34674.4[a]
	Lag	655.1[a]	675.1[a]	582[a]	670.3[a]	628.1[a]	608[a]	650.4[a]	703.9[a]
	RErro	37147.1[a]	34844.4[a]	33603.6[a]	32759.4[a]	36729.2[a]	33798.2[a]	33544.3[a]	34083.3[a]
	RLag	79.2[a]	96.3[a]	69.5[a]	107.1[a]	71.2[a]	78[a]	94.5[a]	112.8[a]
Composite risk (WUI)	Spatial weight matrix = KNN4								
	Error	1197.1[a]	1116.2[a]	974.7[a]	1130.1[a]	1076[a]	919[a]	861[a]	1215.6[a]
	Lag	1590.7[a]	1493.7[a]	1409[a]	1550.1[a]	1398.3[a]	1173.2[a]	1216.9[a]	1615.7[a]
	RErro	166.3[a]	152.6[a]	112.8[a]	146.6[a]	155.1[a]	134.6[a]	103.4[a]	168.1[a]
	RLag	560[a]	530.1[a]	547.1[a]	566.6[a]	477.4[a]	388.7[a]	459.3[a]	568.2[a]
	Spatial weight matrix = KNN8								
	Error	2080.8[a]	1929.3[a]	1662.4[a]	1962.5[a]	1842.4[a]	1538.4[a]	1438.5[a]	2130.5[a]
	Lag	1941.3[a]	1801.8[a]	1684.7[a]	1885.5[a]	1669.7[a]	1358.4[a]	1425.1[a]	1982.2[a]
	RErro	708.3[a]	655.7[a]	526.5[a]	651[a]	640[a]	539.7[a]	461.4[a]	725.5[a]
	RLag	568.8[a]	528.1[a]	548.9[a]	574[a]	467.3[a]	359.6[a]	448.1[a]	577.3[a]
	Spatial weight matrix = DIS0.5								
	Error	4862.7[a]	4434.2[a]	3749.9[a]	4554.8[a]	4251.8[a]	3432.9[a]	3193.5[a]	4977.9[a]
	Lag	418.7[a]	378.9[a]	347.4[a]	385.3[a]	350.2[a]	260.1[a]	303.4[a]	420.7[a]
	RErro	4578[a]	4176.6[a]	3522[a]	4291.6[a]	4011.4[a]	3249.5[a]	2998.1[a]	4689.7[a]
	RLag	134.1[a]	121.3[a]	119.4[a]	122.1[a]	109.7[a]	76.8[a]	108.1[a]	132.5[a]

Table 6.6: LM test results for the aggregate fire measure (Data = Assessed value, Functional form = Double-log) (cont'd)

Wildfire risk data	**LM**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
WUI risk	Spatial weight matrix = KNN4								
	Error	1026.8[a]	1047.5[a]	949.5[a]	1018.9[a]	946.4[a]	867.9[a]	781.9[a]	1057.5[a]
	Lag	1483.1[a]	1467.7[a]	1393.1[a]	1472.9[a]	1314.1[a]	1171.1[a]	1198.2[a]	1497.2[a]
	RError	117.4[a]	128.5[a]	104.7[a]	116.1[a]	117.5[a]	112.3[a]	76.1[a]	126.4[a]
	RLag	573.7[a]	548.6[a]	548.3[a]	570.1[a]	485.3[a]	415.4[a]	492.5[a]	566.1[a]
	Spatial weight matrix = KNN8								
	Error	1746.9[a]	1795.8[a]	1610.5[a]	1743[a]	1593.8[a]	1443.4[a]	1289.9[a]	1814.6[a]
	Lag	1801.5[a]	1777.9[a]	1669.6[a]	1784[a]	1560.9[a]	1360.8[a]	1404[a]	1819.9[a]
	RError	538.2[a]	575.3[a]	495.2[a]	541.5[a]	513.8[a]	475.2[a]	375.2[a]	574.4[a]
	RLag	592.8[a]	557.3[a]	554.2[a]	582.5[a]	480.9[a]	392.6[a]	489.3[a]	579.7[a]
	Spatial weight matrix = DIS0.5								
	Error	3948.8[a]	4071.4[a]	3617.1[a]	3956.2[a]	3579.5[a]	3208.8[a]	2840[a]	4114.8[a]
	Lag	392.7[a]	376[a]	346[a]	367.5[a]	331.6[a]	266.5[a]	307.1[a]	388.7[a]
	RError	3697.4[a]	3823.6[a]	3392.9[a]	3714.7[a]	3362.6[a]	3027.4[a]	2652.5[a]	3860.9[a]
	RLag	141.3[a]	128.2[a]	121.7[a]	126[a]	114.7[a]	85.1[a]	119.5[a]	134.7[a]
House risk	Spatial weight matrix = KNN4								
	Error	109.7[a]	90.3[a]	97[a]	106.6[a]	92.9[a]	91.5[a]	88.9[a]	121.6[a]
	Lag	169.5[a]	134.6[a]	138.4[a]	166.6[a]	139.2[a]	131.2[a]	125.2[a]	177.6[a]
	RError	10.2[a]	9.2[a]	10.3[a]	9.6[a]	9.2[a]	10.1[a]	9.8[a]	12.9[a]
	RLag	70[a]	53.5[a]	51.7[a]	69.6[a]	55.5[a]	49.9[a]	46[a]	68.9[a]
	Spatial weight matrix = KNN8								
	Error	212.6[a]	174.7[a]	184.3[a]	206.3[a]	180.8[a]	183.9[a]	173.4[a]	237.6[a]
	Lag	249.3[a]	199.3[a]	206.6[a]	250.5[a]	208.7[a]	198.9[a]	188.5[a]	266.3[a]
	RError	55.3[a]	46.9[a]	48.4[a]	51.1[a]	47.3[a]	51.7[a]	46.9[a]	63.8[a]
	RLag	92[a]	71.5[a]	70.8[a]	95.2[a]	75.3[a]	66.7[a]	62.1[a]	92.5[a]
	Spatial weight matrix = DIS0.5								
	Error	248.5[a]	206.1[a]	208.7[a]	241.8[a]	212.5[a]	210.2[a]	197[a]	277[a]
	Lag	22[a]	19.1[a]	17.9[a]	21.7[a]	19.1[a]	19.4[a]	17.7[a]	22[a]
	RError	235.4[a]	195[a]	198[a]	228.9[a]	201.3[a]	198.9[a]	186.6[a]	263.2[a]
	RLag	8.9[a]	8.1[a]	7.2[a]	8.8[a]	7.9[a]	8.2[a]	7.4[a]	8.2[a]

[a] significant at 1% level.

Table 6.7: LM test results for the nearest measure (Data = Estimated sale prices)

Wildfire risk data	LM test	Past fire event/occurrence			
		7-yr	15-yr	7-yr	15-yr
		SEMILOG		DOUBLELOG	
Composite risk (County)	Spatial weight matrix = KNN4				
	Error	383.8[a]	367.2[a]	417[a]	392[a]
	Lag	481[a]	457.8[a]	410.6[a]	370.9[a]
	RError	26.1[a]	26[a]	63[a]	65.2[a]
	RLag	123.3[a]	116.6[a]	56.6[a]	44.1[a]
	Spatial weight matrix = KNN8				
	Error	629.2[a]	602.1[a]	673.5[a]	626.8[a]
	Lag	648.2[a]	613.8[a]	541.4[a]	484.3[a]
	RError	125.1[a]	123.5[a]	197.4[a]	193.2[a]
	RLag	144.1[a]	135.2[a]	65.2[a]	50.7[a]
	Spatial weight matrix = DIS0.5				
	Error	955[a]	920.2[a]	1106.2[a]	1038.1[a]
	Lag	46.2[a]	41[a]	41.4[a]	31.9[a]
	RError	924.6[a]	892.4[a]	1076.6[a]	1013.7[a]
	RLag	15.8[a]	13.2[a]	11.8[a]	7.6[a]
Composite risk (Non-WUI)	Spatial weight matrix = KNN4				
	Error	322.3[a]	275.1[a]	346.5[a]	293.8[a]
	Lag	355[a]	323.1[a]	291.4[a]	251.6[a]
	RError	34.7[a]	24.1[a]	74.7[a]	61[a]
	RLag	67.4[a]	72.1[a]	19.6[a]	18.8[a]
	Spatial weight matrix = KNN8				
	Error	561.5[a]	470.4[a]	605.9[a]	502.4[a]
	Lag	510.7[a]	466.3[a]	419.5[a]	358.7[a]
	RError	137.2[a]	100.5[a]	212.5[a]	169.8[a]
	RLag	86.5[a]	96.5[a]	26.1[a]	26.1[a]
	Spatial weight matrix = DIS0.5				
	Error	1099.7[a]	863.6[a]	1280.1[a]	1008.2[a]
	Lag	20.5[a]	11.8[a]	15.1[a]	11.9[a]
	RError	1081[a]	852.2[a]	1265.2[a]	996.5[a]
	RLag	1.9	0.4	0.3	0.3
Composite risk (WUI)	Spatial weight matrix = KNN4				
	Error	18.6[a]	17.3[a]	26.6[a]	26.5[a]
	Lag	52[a]	45.2[a]	55.9[a]	45.9[a]
	RError	1.7	1.2	0.2	0
	RLag	35.1[a]	29[a]	29.5[a]	19.4[a]
	Spatial weight matrix = KNN8				
	Error	18.8[a]	17.4[a]	24.7[a]	25.5[a]
	Lag	59.2[a]	49.6[a]	59.6[a]	47[a]
	RError	0.8	0.4	0	0.3
	RLag	41.1[a]	32.6[a]	35[a]	21.9[a]

Table 6.7: LM test results for the nearest measure (Data = Estimated sale prices) (cont'd)

Wildfire risk data	**LM test**	**Past fire event/occurrence**			
		7-yr	**15-yr**	**7-yr**	**15-yr**
		SEMILOG		**DOUBLELOG**	
	Spatial weight matrix = DIS0.5				
	Error	31.8[a]	33.1[a]	46.6[a]	48.2[a]
	Lag	13.8[a]	10.7[a]	6[b]	2.9[c]
	RError	28.3[a]	30[a]	44.1[a]	46.5[a]
	RLag	10.3[a]	7.5[a]	3.5[c]	1.2
WUI risk	Spatial weight matrix = KNN4				
	Error	17.7[a]	15.5[a]	25.5[a]	21.7[a]
	Lag	51.7[a]	45.2[a]	57[a]	42.7[a]
	RError	2.3	2.2	0.5	0.1
	RLag	36.3[a]	31.8[a]	32[a]	21.1[a]
	Spatial weight matrix = KNN8				
	Error	17.4[a]	14.9[a]	22.9[a]	18.8[a]
	Lag	58.6[a]	49.5[a]	60.9[a]	42.9[a]
	RError	1.4	1.2	0.3	0.03
	RLag	42.6[a]	35.8[a]	38.3[a]	24.1[a]
	Spatial weight matrix = DIS0.5				
	Error	30[a]	29.8[a]	43.7[a]	39.5[a]
	Lag	13[a]	9.8[a]	5.4[b]	1.8
	RError	26.7[a]	27[a]	41.3[a]	38.3[a]
	RLag	9.7[a]	6.9[a]	3.1[c]	0.6
House risk	Spatial weight matrix = KNN4				
	Error	0.1	1.5	0.1	2.6
	Lag	0.9	0.6	0.7	0.5
	RError	2.3	1	2.5	2.8[c]
	RLag	3.2[c]	0.1	3[c]	0.6
	Spatial weight matrix = KNN8				
	Error	0.2	2.9[c]	0.1	3.8[c]
	Lag	1.7	0.6	1.6	0.6
	RError	4.5[b]	3.1[c]	3.8[c]	4.4[b]
	RLag	6[b]	0.9	5.3[b]	1.2
	Spatial weight matrix = DIS0.5				
	Error	0.4	1.2	0.6	2.2
	Lag	0.006	0.004	0.001	0.08
	RError	0.5	1.2	0.6	2.2
	RLag	0.02	0.02	0.0009	0.03

[a] significant at 1% level.
[b] significant at 5% level.
[c] significant at 10% level.

Table 6.8: LM test results for the aggregate fire measure (Data = Estimated sale prices, Functional form = Semi-log)

Wildfire risk data	**LM**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
Composite risk (County)	Spatial weight matrix = KNN4								
	Error	385.8[a]	360.8[a]	345.9[a]	393.8[a]	391.6[a]	369.7[a]	334.5[a]	385.4[a]
	Lag	464.9[a]	450.4[a]	453[a]	471[a]	464.7[a]	446.3[a]	440.6[a]	459.4[a]
	RError	31.5[a]	25.5[a]	19.5[a]	32[a]	33.6[a]	29.9[a]	18.4[a]	31.4[a]
	RLag	110.6[a]	115[a]	126.7[a]	109.2[a]	106.8[a]	106.5[a]	124.5[a]	105.4[a]
	Spatial weight matrix = KNN8								
	Error	633.4[a]	587.9[a]	559.5[a]	649[a]	645.1[a]	601.3[a]	535.7[a]	632.7[a]
	Lag	619.8[a]	597.4[a]	604.3[a]	632.5[a]	620.3[a]	591.2[a]	584.7[a]	616.4[a]
	RError	140.2[a]	121.7[a]	102.9[a]	141.7[a]	146.6[a]	131.7[a]	96.7[a]	137.2[a]
	RLag	126.6[a]	131.2[a]	147.6[a]	125.3[a]	121.9[a]	121.7[a]	145.8[a]	120.9[a]
	Spatial weight matrix = DIS0.5								
	Error	973[a]	897.9[a]	850.4[a]	1002.8[a]	1002.8[a]	924.4[a]	816.9[a]	966.7[a]
	Lag	47.1[a]	40.9[a]	44.2[a]	48.6[a]	47[a]	38.9[a]	42.6[a]	48.3[a]
	RError	942[a]	870.4[a]	822.1[a]	970.8[a]	971.4[a]	897.3[a]	789.7[a]	935.2[a]
	RLag	16.1[a]	13.3[a]	15.9[a]	16.6[a]	15.6[a]	11.8[a]	15.4[a]	16.9[a]
Composite risk (Non-WUI)	Spatial weight matrix = KNN4								
	Error	323.1[a]	318.1[a]	310.4[a]	319.4[a]	318.6[a]	313.3[a]	295[a]	311.1[a]
	Lag	353.4[a]	352.5[a]	353.9[a]	351.3[a]	348.1[a]	348.5[a]	341.6[a]	342.4[a]
	RError	36.1[a]	34[a]	30.1[a]	34.2[a]	35.5[a]	33[a]	27.1[a]	33.2[a]
	RLag	66.4[a]	68.4[a]	73.6[a]	66.1[a]	64.9[a]	68.3[a]	73.6[a]	64.4[a]
	Spatial weight matrix = KNN8								
	Error	564.2[a]	552.9[a]	535.6[a]	557.8[a]	556.6[a]	547.3[a]	506.7[a]	538.7[a]
	Lag	509.6[a]	505.8[a]	509.8[a]	508.7[a]	501[a]	501.8[a]	488.4[a]	493.6[a]
	RError	140.7[a]	135.1[a]	122.6[a]	134.8[a]	139.2[a]	133.4[a]	113.8[a]	128.9[a]
	RLag	86.1[a]	88[a]	96.8[a]	85.6[a]	83.5[a]	87.9[a]	95.5[a]	83.8[a]
	Spatial weight matrix = DIS0.5								
	Error	1115.4[a]	1087.1[a]	1043.5[a]	1103.3[a]	1100.7[a]	1075.2[a]	982.5[a]	1050.8[a]
	Lag	23.6[a]	22.8[a]	28.3[a]	21.5[a]	21[a]	22[a]	27[a]	21.7[a]
	RError	1094.6[a]	1067[a]	1020.2[a]	1084[a]	1081.7[a]	1055.7[a]	960.4[a]	1031.5[a]
	RLag	2.8*	2.7*	5.1[b]	2.2	2.1	2.5	4.9[b]	2.5
Composite risk (WUI)	Spatial weight matrix = KNN4								
	Error	20.6[a]	17.5[a]	18.5[a]	24.8[a]	23.4[a]	17.4[a]	19.2[a]	25.2[a]
	Lag	53[a]	49.1[a]	52.9[a]	62[a]	56.7[a]	45.1[a]	53.1[a]	63[a]
	RError	1.2	1.7	2	1.1	0.9	1.2	1.7	1.1
	RLag	33.5[a]	33.2[a]	36.3[a]	38.4[a]	34.1[a]	28.9[a]	35.6[a]	38.9[a]
	Spatial weight matrix = KNN8								
	Error	20.8[a]	17.4[a]	18.7[a]	29.3[a]	25.8[a]	17.5[a]	20.1[a]	29.9[a]
	Lag	59.5[a]	53.6[a]	60[a]	74.7[a]	64.8[a]	48.6[a]	61[a]	76.3[a]
	RError	0.4	0.6	0.9	0.09	0.07	0.3	0.6	0.1
	RLag	39.1[a]	36.9[a]	42.2[a]	45.5[a]	39[a]	31.4[a]	41.5[a]	46.5[a]
	Spatial weight matrix = DIS0.5								
	Error	36.7[a]	33.8[a]	33.7[a]	45[a]	41.2[a]	35.1[a]	35.7[a]	45.6[a]
	Lag	15.2[a]	12.2[a]	13.8[a]	16.6[a]	14.1[a]	9.7[a]	12.9[a]	16.6[a]
	RError	32.8[a]	30.4[a]	30[a]	40.4[a]	37.2[a]	32.1[a]	32.1[a]	41[a]
	RLag	11.3[a]	8.8[a]	10.2[a]	12[a]	10.1[a]	6.6**	9.3[a]	12[a]

Table 6.8: LM test results for the aggregate fire measure (Data = Estimated sale prices, Functional form = Semi-log) (cont'd)

Wildfire risk data	**LM test**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
WUI risk	Spatial weight matrix = KNN4								
	Error	18.9[a]	17.2[a]	17.4[a]	21.8[a]	20.2[a]	16.5[a]	17.3[a]	22.4[a]
	Lag	52.3[a]	50.1[a]	53.2[a]	59.4[a]	54.4[a]	46.6[a]	53.5[a]	59.7[a]
	RError	1.9	2.3	2.8[c]	2	1.8	2	2.9[c]	1.8
	RLag	35.3[a]	35.2[a]	38.6[a]	39.7[a]	36[a]	32[a]	39.2[a]	39.2[a]
	Spatial weight matrix = KNN8								
	Error	18.2[a]	16.8[a]	17.1[a]	24.3[a]	20.8[a]	16.2[a]	17.3[a]	25.2[a]
	Lag	58.4[a]	54.9[a]	60.5[a]	70.4[a]	61.6[a]	50.2[a]	61.4[a]	71.1[a]
	RError	1.1	1.1	1.8	0.7	0.8	0.9	1.8	0.6
	RLag	41.3[a]	39.2[a]	45.2[a]	46.8[a]	41.6[a]	35[a]	45.9[a]	46.5[a]
	Spatial weight matrix = DIS0.5								
	Error	33.5[a]	32.4[a]	31.5[a]	39.5[a]	35.9[a]	32.9[a]	32.1[a]	40.3[a]
	Lag	14.1[a]	11.7[a]	13[a]	14.9[a]	12.6[a]	9.1[a]	11.9[a]	15[a]
	RError	29.9[a]	29.2[a]	28.1[a]	35.4[a]	32.4[a]	30[a]	28.8[a]	36.2[a]
	RLag	10.4[a]	8.5[a]	9.6[a]	10.8[a]	9[a]	6.2[b]	8.6[a]	10.9[a]
House risk	Spatial weight matrix = KNN4								
	Error	0.1	0.6	0.05	0.8	0.3	0.4	0.4	0.09
	Lag	1.2	0.4	2.3	1.7	1.2	0.1	0.5	0.3
	RError	0.5	3.9[b]	2.3	0.04	0.3	0.4	3.1[c]	0.03
	RLag	1.5	3.7[c]	4.5[b]	1	1.2	0.06	3.2[c]	0.2
	Spatial weight matrix = KNN8								
	Error	0.2	1.1	0.01	0.9	0.6	1.6	1.3	0.001
	Lag	2.6	0.8	3.8[c]	4.3[b]	2.7	0.01	0.9	1.2
	RError	1.7	7.4[a]	5.1[b]	1	0.5	3.6[c]	8.1[a]	1.7
	RLag	4.1[b]	7.1[a]	8.9[a]	4.4[b]	2.6	2	7.7[a]	2.9[c]
	Spatial weight matrix = DIS0.5								
	Error	0.04	0.4	0.02	0.05	0.1	0.1	0.4	0.008
	Lag	0.04	0.2	0.2	1	0.07	0.08	0.2	0.9
	RError	0.03	0.4	0.04	0.02	0.08	0.2	0.5	0.03
	RLag	0.04	0.2	0.2	0.9	0.06	0.1	0.3	0.9

[a] significant at 1% level.
[b] significant at 5% level.
[c] significant at 10% level.

Table 6.9: LM test results for the aggregate fire measure (Data = Estimated sale prices, Functional form = Double-log)

Wildfire risk data	LM	Past fire event/occurrence							
		7-yr time window				15-yr time window			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
Composite risk (County)	Spatial weight matrix = KNN4								
	Error	426.2[a]	395.6[a]	381.4[a]	435.5[a]	432.6[a]	402.8[a]	368.8[a]	420.7[a]
	Lag	409.4[a]	386.6[a]	388.1[a]	422.5[a]	416.3[a]	384.4[a]	380.5[a]	407.6[a]
	RError	68.5[a]	60.8[a]	52.5[a]	67.4[a]	68.7[a]	65.2[a]	48.5[a]	64.9[a]
	RLag	51.8[a]	51.8[a]	59.2[a]	54.4[a]	52.4[a]	46.9[a]	60.2[a]	51.8[a]
	Spatial weight matrix = KNN8								
	Error	690.5[a]	635.9[a]	608.7[a]	709.2[a]	704.6[a]	645.6[a]	582.3[a]	680.8[a]
	Lag	536.4[a]	501.6[a]	506.7[a]	557.2[a]	547.3[a]	499.4[a]	494.7[a]	535.3[a]
	RError	212.1[a]	191.3[a]	169.7[a]	212.5[a]	215.4[a]	198.1[a]	157[a]	202.7[a]
	RLag	58[a]	57[a]	67.7[a]	60.5[a]	58.1[a]	51.8[a]	69.4[a]	57.3[a]
	Spatial weight matrix = DIS0.5								
	Error	1153.9[a]	1060.1[a]	1009.4[a]	1188.2[a]	1189.3[a]	1083.4[a]	972.4[a]	1126.6[a]
	Lag	41.8[a]	35.5[a]	40.8[a]	43.6[a]	39.9[a]	32[a]	38.7[a]	42.6[a]
	RError	1123.6[a]	1033.7[a]	981.1[a]	1156.8[a]	1159.6[a]	1058.5[a]	945.4[a]	1096.1[a]
	RLag	11.5[a]	9.1[a]	12.5[a]	12.1[a]	10.2[a]	7.1[a]	11.6[a]	12.1[a]
Composite risk (Non-WUI)	Spatial weight matrix = KNN4								
	Error	345.8[a]	339.5[a]	328.7[a]	341.2[a]	336.7[a]	334.5[a]	308.4[a]	330.3[a]
	Lag	289.3[a]	286.8[a]	283.4[a]	289.5[a]	286.3[a]	288.8[a]	271.9[a]	281.3[a]
	RError	75.4[a]	72.3[a]	67.1[a]	71.8[a]	70.6[a]	67.5[a]	59.6[a]	68.8[a]
	RLag	18.9[a]	19.7[a]	21.8[a]	20.1[a]	20.2[a]	21.9[a]	23.1[a]	19.9[a]
	Spatial weight matrix = KNN8								
	Error	608.8[a]	593.9[a]	570.4[a]	600.6[a]	593.5[a]	588.1[a]	533.2[a]	577.7[a]
	Lag	418.1[a]	411.7[a]	408.6[a]	419[a]	412.2[a]	416.5[a]	388.7[a]	404.9[a]
	RError	215.9[a]	208[a]	191.8[a]	208[a]	207.3[a]	199.9[a]	175.2[a]	198.8[a]
	RLag	25.1[a]	25.8[a]	30.1[a]	26.5[a]	26[a]	28.3[a]	30.7[a]	26[a]
	Spatial weight matrix = DIS0.5								
	Error	1290[a]	1248.3[a]	1185.3[a]	1271.8[a]	1259[a]	1238.2[a]	1108.3[a]	1210.8[a]
	Lag	16.2[a]	15.8[a]	20.3[a]	14.8[a]	13.9[a]	14.8[a]	18.8[a]	14.6[a]
	RError	1274.3[a]	1233[a]	1166.6[a]	1257.3[a]	1245.3[a]	1223.7[a]	1091.1[a]	1196.5[a]
	RLag	0.5	0.5	1.7	0.3	0.2	0.3	1.5	0.3
Composite risk (WUI)	Spatial weight matrix = KNN4								
	Error	29.3[a]	27.6[a]	27.8[a]	34.4[a]	33.3[a]	27[a]	28.9[a]	34.6[a]
	Lag	60.1[a]	57.7[a]	60.9[a]	70.1[a]	64.4[a]	54.3[a]	61.6[a]	70.9[a]
	RError	0.1	0.2	0.4	0.1	0.03	0.1	0.3	0.2
	RLag	30.9[a]	30.3[a]	33.5[a]	35.7[a]	31.1[a]	27.4[a]	33[a]	36.5[a]
	Spatial weight matrix = KNN8								
	Error	26.8[a]	26[a]	26.4[a]	37.2[a]	33.6[a]	25.8[a]	28.3[a]	37.3[a]
	Lag	64[a]	60.7[a]	66.2[a]	80.7[a]	70.3[a]	56.6[a]	68[a]	81.9[a]
	RError	0.01	0.002	0.08	0.06	0.1	0.003	0.02	0.04
	RLag	37.2[a]	34.7[a]	39.9[a]	43.6[a]	36.7[a]	30.8[a]	39.7[a]	44.7[a]
	Spatial weight matrix = DIS0.5								
	Error	53.7[a]	53.1[a]	51[a]	62.6[a]	60.3[a]	53.3[a]	53.4[a]	62.5[a]
	Lag	8.1[a]	6[b]	7.2[a]	10.3[a]	7.5[a]	4.8[b]	7[a]	10.6[a]
	RError	50.5[a]	50.4[a]	48.1[a]	58.6[a]	57.1[a]	50.9[a]	50.5[a]	58.6[a]
	RLag	4.9[b]	3.3[c]	4.3[b]	6.4[b]	4.3[b]	2.4	4.1[b]	6.6[b]

Table 6.9: LM test results for the aggregate fire measure (Data = Estimated sale prices, Functional form = Double-log) (cont'd)

Wildfire	**LM test**	**Past fire event/occurrence**							
		7-yr time window				**15-yr time window**			
		10km	**15km**	**20km**	**25km**	**10km**	**15km**	**20km**	**25km**
WUI risk	Spatial weight matrix = KNN4								
	Error	28.1[a]	27.4[a]	26.4[a]	31.5[a]	30.1[a]	26.1[a]	26.8[a]	32[a]
	Lag	60.7[a]	59.6[a]	62[a]	68.7[a]	63.2[a]	56[a]	62.7[a]	69[a]
	RError	0.4	0.4	0.9	0.5	0.3	0.4	0.8	0.4
	RLag	33[a]	32.6[a]	36.5[a]	37.7[a]	33.4[a]	30.3[a]	36.7[a]	37.5[a]
	Spatial weight matrix = KNN8								
	Error	25[a]	25.5[a]	24.3[a]	32.5[a]	28.7[a]	24.2[a]	25.2[a]	33.1[a]
	Lag	65[a]	63.2[a]	68[a]	78.6[a]	68.8[a]	58.6[a]	69.4[a]	78.9[a]
	RError	0.2	0.1	0.5	0.07	0.06	0.1	0.5	0.05
	RLag	40.3[a]	37.8[a]	44.3[a]	46.1[a]	40.1[a]	34.4[a]	44.6[a]	45.9[a]
	Spatial weight matrix = DIS0.5								
	Error	50.9[a]	51.6[a]	47.9[a]	56.7[a]	54.5[a]	50.6[a]	49.1[a]	57.1[a]
	Lag	7.5[a]	5.8[b]	6.8[a]	9[a]	6.6[b]	4.3[b]	6.3[b]	9.3[a]
	RError	47.9[a]	49[a]	45.2[a]	53.2[a]	51.6[a]	48.4[a]	46.4[a]	53.5[a]
	RLag	4.5[b]	3.2[c]	4[b]	5.5[b]	3.7[c]	2.1	3.6[c]	5.7[b]
House risk	Spatial weight matrix = KNN4								
	Error	0.03	1	0.04	0.6	0.1	0.7	0.2	0.04
	Lag	0.9	0.1	2.2	2	0.7	0.2	0.6	0.5
	RError	0.7	3.9[b]	2.3	0.2	0.3	0.6	2.4	0.3
	RLag	1.6	3[c]	4.5[b]	1.6	0.9	0.1	2.8[c]	0.7
	Spatial weight matrix = KNN8								
	Error	0.2	1.3	0.05	1.4	0.5	1.5	0.5	0.06
	Lag	2.3	0.4	3.9[b]	5.3[b]	2	0.02	1.2	1.9
	RError	1.4	6.6[b]	4.6[b]	0.9	0.4	3.1[c]	6.3[b]	1.7
	RLag	3.5[c]	5.7[b]	8.4[a]	4.8[b]	1.9	1.6	7[a]	3.5[c]
	Spatial weight matrix = DIS0.5								
	Error	0.01	0.6	0.03	0.07	0.05	0.3	0.3	0.007
	Lag	0.04	0.006	0.002	0.2	0.01	0.07	0.03	0.3
	RError	0.02	0.6	0.03	0.05	0.05	0.2	0.3	0.02
	RLag	0.04	0.0003	0.004	0.2	0.01	0.05	0.02	0.3

[a] significant at 1% level.
[b] significant at 5% level.
[c] significant at 10% level.

Table 6.10: The preferred model specification based on LM test results

Wildfire risk data	Weight matrix		
	KNN4	**KNN8**	**DIS0.5**
Composite risk covering County or Non-WUI area	Lag[a] for semi-log, Error for double-log	Error[b]	Error
Composite risk covering WUI area or WUI risk	Lag	Lag[c]	Error
House level risk	OLS for estimated sale prices data[d], Lag for assessed value data	OLS for estimated sale prices data[e], Lag for assessed value data	OLS for estimated sale prices data, Error for assessed value data

[a] One exception is the preferred model specification is spatial error model for HP_AV&AGG720&COMP_NWUI&KNN4&SEMILOG.

[b] The exceptions are the preferred model specification is spatial lag model for HP_ESP&AGG715&COMP_CT&KNN8&SEMILOG and HP_ESP&AGG720&COMP_CT&KNN8&SEMILOG.

[c] The exceptions are the preferred model specification is spatial error model for HP_AV&NEAR15&COMP_WUI&KNN8&DOUBLELOG, HP_AV&NEAR15&WUIRISK&KNN8&DOUBLELOG, HP_AV&AGG710&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG715&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG725&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG1510&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG1515&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG1525&COM_WUI&KNN8&DOUBLELOG, HP_AV&AGG715&WUIRISK&KNN8&DOUBLELOG and HP_AV&AGG1510&WUIRISK&KNN8&DOUBLELOG and HP_AV&AGG1515&WUIRISK&KNN8&DOUBLELOG;

[d] One exception is the preferred model specification is spatial error model for HP_ESP&NEAR15&HRISK&KNN4&DOUBLELOG.

[e] The exceptions are the preferred model specification is spatial lag model for HP_ESP&AGG720&HRISK&KNN8&DOUBLELOG and HP_ESP&AGG725&HRISK&KNN8&DOUBLELOG; and spatial error model for HP_ESP&NEAR15&HRISK&KNN8&SEMILOG and HP_ESP&NEAR15&HRISK&KNN8&DOUBLELOG.

Table 6.11: Calculation of the marginal implicit price

Model	**Type of variable**	**Marginal implicit price**	
Functional form = Semi-log			
OLS/SEM	Continuous variable. E.g., *Dist*	$\widehat{\beta_C} * \bar{P}$	$\widehat{\beta_C}$ is the estimated coefficient on continuous variable, $\bar{P}$ is the average housing value for the sample population.
	Dummy variable E.g., *Comp_high* and *Comp_ext*	$(e^{\widehat{\beta_D}} - 1) * \bar{P}$	$\widehat{\beta_D}$ is the estimated coefficient on dummy variable
SLM/GSM	Continuous variable	$\frac{1}{(1-\rho)} * \widehat{\beta_C} * \bar{P}$	ρ is the coefficient on the spatially correlated dependent variable
	Dummy variable	$(e^{\frac{1}{(1-\rho)} * \widehat{\beta_D}} - 1) * \bar{P}$	
Functional form = Double-log[a]			
OLS/SEM	Continuous variable that is log-transformed	$\widehat{\beta_C} * \frac{\bar{P}}{\bar{x}}$	$\bar{x}$ is the average characteristics for the sample population.
SLM/GSM	Continuous variable that is log-transformed	$\frac{1}{(1-\rho)} * \widehat{\beta_C} * \frac{\bar{P}}{\bar{x}}$	

[a] For dummy variables and continuous variables that are not log-transformed, the formula for calculating the marginal implicit price estimate in double-log models is the same as that in the semi-log models.

Table 6.12: Hedonic regression results for model 1 with Composite risk (County)

Variables	No spatial OLS		SEM					
			KNN4		KNN8		DIS0.5	
		MIP($)		MIP($)		MIP($)		MIP($)
Constant	6.319 ^{a}		6.533^{a}		6.555^{a}		6.452^{a}	
	(0.059)		(0.067)		(0.079)		(0.156)	
Ln(Area)	0.519^{a}		0.487^{a}		0.48^{a}		0.473^{a}	
	(0.006)		(0.005)		(0.005)		(0.005)	
Ln(Land)	0.03^{a}		0.058^{a}		0.07^{a}		0.079^{a}	
	(0.002)		(0.002)		(0.002)		(0.003)	
Bedroom	0.02^{a}		0.018^{a}		0.018^{a}		0.018^{a}	
	(0.002)		(0.002)		(0.002)		(0.002)	
Bathroom	0.019^{a}		0.018^{a}		0.018^{a}		0.018^{a}	
	(0.002)		(0.002)		(0.002)		(0.002)	
Fireplace	0.086^{a}		0.066^{a}		0.062^{a}		0.065^{a}	
	(0.004)		(0.003)		(0.003)		(0.003)	
Aircond	0.101^{a}		0.078^{a}		0.072^{a}		0.073^{a}	
	(0.007)		(0.006)		(0.006)		(0.006)	
Evapcool	-0.014^{a}		0.00002		0.0004		-0.002	
	(0.005)		(0.005)		(0.005)		(0.005)	
Othercool	0.05^{a}		0.044^{a}		0.041^{a}		0.047^{a}	
	(0.005)		(0.005)		(0.005)		(0.005)	
Phycond	0.28^{a}		0.249^{a}		0.24^{a}		0.225^{a}	
	(0.002)		(0.002)		(0.002)		(0.002)	
Highsch	0.655^{a}		0.745^{a}		0.761^{a}		0.54^{a}	
	(0.026)		(0.037)		(0.046)		(0.062)	
Over65	0.579^{a}		0.723^{a}		0.736^{a}		0.325^{a}	
	(0.028)		(0.041)		(0.049)		(0.064)	
White	-0.004		-0.032		-0.037		0.022	
	(0.035)		(0.049)		(0.059)		(0.086)	
Ln(Highway)	0.011^{a}		0.011^{a}		0.013^{a}		0.016^{a}	
	(0.002)		(0.002)		(0.003)		(0.003)	
City	0.004^{a}		0.007^{a}		0.007^{a}		-0.012^{a}	
	(0.002)		(0.002)		(0.003)		(0.004)	
Lake	-0.018^{a}		-0.019^{a}		-0.02^{a}		-0.02^{a}	
	(0.0005)		(0.0007)		(0.0009)		(0.002)	
Forest	-0.015^{a}		-0.018^{a}		-0.02^{a}		-0.023^{a}	
	(0.001)		(0.0009)		(0.001)		(0.002)	
Industry	-0.005^{a}		-0.007^{a}		-0.008^{a}		-0.004^{c}	
	(0.001)		(0.0009)		(0.001)		(0.002)	
WUI	-0.009	-2,931	-0.016^{b}	-5,056	-0.019^{b}	-5,806	0.04^{a}	12,834
	(0.006)		(0.008)		(0.009)		(0.014)	
LN(Dist)	0.121^{a}	1,881	0.074^{a}	1,156	0.06^{a}	930	0.113^{b}	1,756
	(0.012)		(0.015)		(0.019)		(0.048)	

Table 6.12: Hedonic regression results for model 1 with Composite risk (County) (cont'd)

Variables	No spatial OLS		SEM					
			KNN4		KNN8		DIS0.5	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Timesincefire	-0.005[a] (0.0002)	-1,495	-0.006[a] (0.0003)	-1,740	-0.006[a] (0.0004)	-1,789	-0.004[a] (0.0008)	-1,248
Ln(Size)	-0.007[a] (0.001)	-0.35	-0.008[a] (0.002)	-0.41	-0.008[a] (0.002)	-0.42	0.011[a] (0.004)	0.56
Comp_high	0.041[a] (0.004)	13,311	0.023[a] (0.004)	7,275	0.014[a] (0.004)	4,475	0.014[a] (0.004)	4,328
Comp_ext	0.094[a] (0.011)	31,082	0.028[a] (0.01)	8,932	0.011 (0.01)	3,526	-0.003 (0.01)	-975
Lambda			0.461[a] (0.011)		0.541[a] (0.016)		0.84[a] (0.06)	
Adj. R sqr	0.77							
N	41,004							

Data = Assessed value
Past wildfire event/occurrence = the nearest fire burned in the last 7 years
Wildfire risk = Composite risk covering the County
Functional form = Double-log

[a], [b] and [c] denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.13: Hedonic regression results for model 1 with Composite risk (Non-WUI)

Variables	**No spatial OLS**		**SEM**					
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Constant	7.015[a] (0.08)		7.181[a] (0.098)		7.137[a] (0.117)		6.294[a] (0.396)	
Ln(Area)	0.506[a] (0.008)		0.468[a] (0.006)		0.463[a] (0.006)		0.46[a] (0.006)	
Ln(Land)	0.026[a] (0.003)		0.052[a] (0.003)		0.062[a] (0.003)		0.063[a] (0.003)	
Bedroom	0.028[a] (0.003)		0.024[a] (0.002)		0.023[a] (0.002)		0.022[a] (0.002)	
Bathroom	0.017[a] (0.003)		0.019[a] (0.002)		0.019[a] (0.002)		0.019[a] (0.002)	
Fireplace	0.075[a] (0.004)		0.058[a] (0.004)		0.055[a] (0.004)		0.062[a] (0.004)	
Aircond	0.092[a] (0.008)		0.073[a] (0.007)		0.068[a] (0.007)		0.072[a] (0.007)	
Evapcool	-0.021[a] (0.005)		-0.004 (0.005)		-0.0037 (0.005)		-0.007 (0.005)	
Othercool	0.051[a] (0.005)		0.044[a] (0.005)		0.041[a] (0.005)		0.048[a] (0.005)	
Phycond	0.241[a] (0.003)		0.228[a] (0.003)		0.224[a] (0.003)		0.218[a] (0.003)	
Highsch	0.835[a] (0.028)		0.919[a] (0.039)		0.931[a] (0.048)		0.465[a] (0.073)	
Over65	0.259[a] (0.033)		0.319[a] (0.045)		0.341[a] (0.055)		0.07 (0.077)	
White	0.125[b] (0.055)		0.15[c] (0.077)		0.164[c] (0.093)		0.635[a] (0.138)	
Ln(Highway)	0.009[a] (0.002)		0.009[a] (0.003)		0.011[a] (0.003)		0.013[a] (0.004)	
City	0.017[a] (0.004)		0.018[a] (0.004)		0.017[a] (0.005)		-0.011 (0.009)	
Lake	-0.023[a] (0.001)		-0.026[a] (0.001)		-0.027[a] (0.001)		-0.02[a] (0.005)	
Forest	-0.017[a] (0.001)		-0.019[a] (0.001)		-0.019[a] (0.002)		-0.021[a] (0.006)	
Industry	-0.004[a] (0.001)		-0.006[a] (0.002)		-0.008[a] (0.002)		-0.01[c] (0.006)	
LN(Dist)	-0.102[a] (0.018)	-1,428	-0.131[a] (0.024)	-1,838	-0.125[a] (0.03)	-1,756	0.082 (0.132)	1,152
Timesincefire	-0.005[a] (0.0003)	-1,386	-0.005[a] (0.0004)	-1,512	-0.006[a] (0.0005)	-1,573	0.00007 (0.001)	20

Table 6.13: Hedonic regression results for model 1 with Composite risk (Non-WUI) (cont'd)

Variables	**No spatial OLS**		**SEM**					
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Ln(Size)	-0.003 (0.002)	-0.12	-0.006[b] (0.003)	-0.25	-0.006[c] (0.003)	-0.26	0.011[c] (0.006)	0.49
Comp_high	0.074[a] (0.005)	21,481	0.041[a] (0.005)	11,672	0.027[a] (0.005)	7,784	0.019[a] (0.005)	5,467
Comp_ext	0.13[a] (0.012)	38,900	0.051[a] (0.011)	14,726	0.031[a] (0.011)	8,885	0.006 (0.011)	1,627
Lambda			0.411[a] (0.013)		0.539[a] (0.019)		0.959[a] (0.151)	
Adj. R sqr	0.76							
N	29,509							

Data = Assessed value
Past wildfire event/occurrence = the nearest fire burned in the last 7 years
Wildfire risk = Composite risk covering Non-WUI area
Functional form = Double-log

[a], [b] and [c] denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.14: Hedonic regression results for model 1 with Composite risk (WUI)

Variables	**No spatial OLS**		**SLM**		**SLM**		**SEM**	
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Constant	6.34^{a}		3.908^{a}		3.65^{a}		6.414^{a}	
	(0.124)		(0.158)		(0.164)		(0.19)	
Ln(Area)	0.53^{a}		0.502^{a}		0.503^{a}		0.507^{a}	
	(0.011)		(0.011)		(0.011)		(0.009)	
Ln(Land)	0.091^{a}		0.07^{a}		0.072^{a}		0.118^{a}	
	(0.004)		(0.004)		(0.004)		(0.005)	
Bedroom	0.007^{b}		0.01^{a}		0.01^{a}		0.01^{a}	
	(0.004)		(0.003)		(0.003)		(0.003)	
Bathroom	0.016^{a}		0.017^{a}		0.017^{a}		0.014^{a}	
	(0.004)		(0.004)		(0.004)		(0.003)	
Fireplace	0.094^{a}		0.082^{a}		0.081^{a}		0.075^{a}	
	(0.008)		(0.007)		(0.007)		(0.007)	
Aircond	0.092^{a}		0.065^{a}		0.063^{a}		0.075^{a}	
	(0.011)		(0.011)		(0.011)		(0.011)	
Evapcool	0.016^{c}		0.009		0.011		0.013	
	(0.009)		(0.009)		(0.009)		(0.009)	
Othercool	0.047^{a}		0.037^{a}		0.037^{a}		0.041^{a}	
	(0.009)		(0.009)		(0.009)		(0.009)	
Phycond	0.298^{a}		0.238^{a}		0.236^{a}		0.242^{a}	
	(0.004)		(0.005)		(0.005)		(0.004)	
Highsch	-0.296^{a}		-0.259^{a}		-0.27^{a}		-0.213	
	(0.083)		(0.08)		(0.08)		(0.148)	
Over65	1.721^{a}		0.965^{a}		0.864^{a}		1.897^{a}	
	(0.082)		(0.081)		(0.081)		(0.144)	
White	-0.642^{a}		-0.386^{a}		-0.347^{a}		-0.678^{a}	
	(0.058)		(0.055)		(0.056)		(0.102)	
Ln(Highway)	0.03^{a}		0.024^{a}		0.024^{a}		0.027^{a}	
	(0.003)		(0.003)		(0.003)		(0.006)	
City	-0.005^{c}		-0.01^{a}		-0.012^{a}		-0.008^{b}	
	(0.002)		(0.002)		(0.002)		(0.004)	
Lake	-0.007^{a}		-0.006^{a}		-0.007^{a}		-0.004^{b}	
	(0.001)		(0.0008)		(0.0008)		(0.002)	
Forest	-0.016^{a}		-0.009^{a}		-0.008^{a}		-0.022^{a}	
	(0.001)		(0.001)		(0.001)		(0.003)	
Industry	-0.001		0.002^{c}		0.002^{c}		-0.005^{b}	
	(0.001)		(0.0009)		(0.001)		(0.002)	
LN(Dist)	0.216^{a}	4,173	0.157^{a}	4,018	0.152^{a}	3,976	0.215^{a}	4,145
	(0.021)		(0.02)		(0.02)		(0.042)	
Timesincefire	-0.002^{a}	-752	-0.0009^{c}	-459	-0.0007	-395	-0.004^{a}	-1,586
	(0.001)		(0.0005)		(0.0005)		(0.0009)	

Table 6.14: Hedonic regression results for model 1 with Composite risk (WUI) (cont'd)

Variables	**No spatial OLS**		**SLM**		**SLM**		**SEM**	
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Ln(Size)	-0.022[a] (0.003)	-1.42	-0.017[a] (0.002)	-1.45	-0.016[a] (0.002)	-1.42	-0.013[b] (0.005)	-0.82
Comp_high	-0.023[a] (0.007)	-9,097	-0.025[a] (0.007)	-12,945	-0.026[a] (0.007)	-14,000	-0.011 (0.007)	-4,509
Comp_ext	-0.014 (0.023)	-5,553	-0.026 (0.021)	-13,793	-0.033 (0.021)	-17,581	-0.037 (0.022)	-14,616
Spatial Coefficient†			0.244[a] (0.012)		0.264[a] (0.012)		0.612[a] (0.067)	
Adj. R sqr	0.80							
N	11,495							

Data = Assessed value
Past wildfire event/occurrence = the nearest fire burned in the last 7 years
Wildfire risk = Composite risk covering WUI area
Functional form = Double-log

[a], [b] and [c] denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.
† If the preferred alternative is spatial lag model, then spatial correlation coefficient is rho. If it is spatial error model, then spatial correlation coefficient is lambda.

Table 6.15: Hedonic regression results for model 1 with WUI risk

Variables	**No spatial OLS**		**SLM**		**SLM**		**SEM**	
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Constant	6.244[a] (0.124)		3.836[a] (0.156)		3.552[a] (0.161)		6.408[a] (0.185)	
Ln(Area)	0.533[a] (0.011)		0.506[a] (0.011)		0.506[a] (0.011)		0.507[a] (0.009)	
Ln(Land)	0.095[a] (0.004)		0.073[a] (0.004)		0.074[a] (0.004)		0.119[a] (0.004)	
Bedroom	0.008[b] (0.003)		0.011[a] (0.003)		0.01[a] (0.003)		0.01[a] (0.003)	
Bathroom	0.014[a] (0.004)		0.016[a] (0.004)		0.016[a] (0.004)		0.014[a] (0.003)	
Fireplace	0.094[a] (0.008)		0.082[a] (0.007)		0.081[a] (0.007)		0.076[a] (0.007)	
Aircond	0.101[a] (0.011)		0.073[a] (0.011)		0.071[a] (0.011)		0.076[a] (0.011)	
Evapcool	0.017[c] (0.009)		0.011 (0.009)		0.012 (0.009)		0.014 (0.009)	
Othercool	0.053[a] (0.009)		0.041[a] (0.009)		0.041[a] (0.009)		0.042[a] (0.009)	
Phycond	0.294[a] (0.004)		0.236[a] (0.005)		0.234[a] (0.005)		0.243[a] (0.004)	
Highsch	-0.15[c] (0.084)		-0.165[b] (0.081)		-0.181[b] (0.081)		-0.126 (0.145)	
Over65	1.682[a] (0.086)		0.977[a] (0.084)		0.876[a] (0.085)		1.848[a] (0.145)	
White	-0.545[a] (0.059)		-0.324[a] (0.056)		-0.287[a] (0.057)		-0.613[a] (0.1)	
Ln(Highway)	0.021[a] (0.003)		0.017[a] (0.003)		0.017[a] (0.003)		0.022[a] (0.005)	
City	0.003 (0.003)		-0.003 (0.002)		-0.005[c] (0.003)		-0.002 (0.004)	
Lake	-0.009[a] (0.001)		-0.008[a] (0.0009)		-0.009[a] 0.0009)		-0.005[a] (0.002)	
Forest	-0.017[a] (0.002)		-0.01[a] (0.001)		-0.009[a] (0.002)		-0.023[a] (0.003)	
Industry	-0.001 (0.001)		0.0002 (0.001)		0.0001 (0.001)		-0.005[b] (0.002)	
Ln(Dist)	0.167[a] (0.022)	3,229	0.13[a] (0.021)	3,329	0.127[a] (0.021)	3,336	0.173[a] (0.042)	3,346
Timesincefire	-0.004[a] (0.001)	-1,475	-0.002[a] (0.0005)	-1,219	-0.002[a] (0.0005)	-1,157	-0.005[a] (0.0009)	-2,145

Table 6.15: Hedonic regression results for model 1 with WUI risk (cont'd)

Variables	**No spatial OLS**		**SLM**		**SLM**		**SEM**	
			KNN4		**KNN8**		**DIS0.5**	
		MIP($)		**MIP($)**		**MIP($)**		**MIP($)**
Ln(Size)	-0.025[a] (0.003)	-1.66	-0.02[a] (0.002)	-1.71	-0.019[a] (0.002)	-1.68	-0.016[a] (0.005)	-1.07
WUI_high	0.084[a] (0.012)	35,251	0.08[a] (0.011)	45,053	0.082[a] (0.011)	47,492	0.067[a] (0.02)	27,783
WUI_vhigh	-0.115[a] (0.02)	-43,845	-0.063[a] (0.019)	-32,533	-0.057[a] (0.019)	-30,083	-0.118[a] (0.034)	-44,878
WUI_ext	0.006 (0.024)	2,564	-0.01 (0.022)	-5,143	-0.016 (0.022)	-8,571	0.005 (0.045)	1,925
Spatial Coefficient†			0.243[a] (0.011)		0.265[a] (0.012)		0.594[a] (0.071)	
Adj. R sqr	0.81							
N	11,495							

Data = Assessed value
Past wildfire event/occurrence = the nearest fire burned in the last 7 years
Wildfire risk = WUI risk
Functional form = Double-log

[a], [b] and [c] denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.
† If the preferred alternative is spatial lag model, then spatial correlation coefficient is rho. If it is spatial error model, then spatial correlation coefficient is lambda.

Table 6.16: Hedonic regression results for model 1 with House level risk

Variables	No spatial OLS		SLM		SLM		SEM	
			KNN4		KNN8		DIS0.5	
		MIP($)		MIP($)		MIP($)		MIP($)
Constant	5.522[a]		3.231[a]		2.491[a]		5.606[a]	
	(0.438)		(0.514)		(0.519)		(0.52)	
Ln(Area)	0.461[a]		0.451[a]		0.449[a]		0.45[a]	
	(0.03)		(0.028)		(0.028)		(0.025)	
Ln(Land)	0.125[a]		0.107[a]		0.105[a]		0.124[a]	
	(0.015)		(0.015)		(0.015)		(0.014)	
Bedroom	-0.007		-0.006		-0.005		-0.003	
	(0.01)		(0.01)		(0.009)		(0.008)	
Bathroom	0.021[c]		0.02[c]		0.022[b]		0.019[b]	
	(0.012)		(0.011)		(0.011)		(0.01)	
Fireplace	0.111[a]		0.103[a]		0.101[a]		0.113[a]	
	(0.023)		(0.022)		(0.022)		(0.021)	
Aircond	0.151[a]		0.121[a]		0.114[a]		0.129[a]	
	(0.04)		(0.039)		(0.037)		(0.041)	
Evapcool	0.059[c]		0.065[b]		0.058[c]		0.053	
	(0.035)		(0.033)		(0.033)		(0.034)	
Othercool	0.029		0.049[c]		0.052[c]		0.034	
	(0.031)		(0.03)		(0.029)		(0.029)	
Phycond	0.286[a]		0.245[a]		0.232[a]		0.255[a]	
	(0.011)		(0.012)		(0.012)		(0.012)	
Highsch	-0.724[a]		-0.412		-0.339		-0.636[c]	
	(0.264)		(0.269)		(0.264)		(0.364)	
Over65	0.522[b]		0.119		-0.021		0.664[c]	
	(0.264)		(0.26)		(0.258)		(0.393)	
White	0.425		0.281		0.26		0.344	
	(0.286)		(0.286)		(0.286)		(0.338)	
Ln(Highway)	0.029[b]		0.019		0.015		0.028	
	(0.014)		(0.014)		(0.013)		(0.018)	
City	-0.002		-0.003		-0.004		-0.003	
	(0.008)		(0.008)		(0.007)		(0.012)	
Lake	-0.005		-0.004		-0.004		-0.005	
	(0.004)		(0.003)		(0.003)		(0.005)	
Forest	-0.049[a]		-0.034[a]		-0.03[a]		-0.052[a]	
	(0.005)		(0.005)		(0.005)		(0.006)	
Industry	0.003		0.004		0.004		0.003	
	(0.003)		(0.003)		(0.003)		(0.005)	
WUI	0.137[a]	46,323	0.1[a]	43,074	0.092[a]	43,607	0.119[a]	39,866
	(0.035)		(0.033)		(0.032)		(0.042)	
Ln(Dist)	0.428[a]	6,654	0.329[a]	6,586	0.301[a]	6,599	0.46[a]	7,158
	(0.062)		(0.059)		(0.059)		(0.093)	

Table 6.16: Hedonic regression results for model 1 with House level risk (cont'd)

Variables	No spatial OLS		SLM		SLM		SEM	
			KNN4		KNN8		DIS0.5	
		MIP($)		MIP($)		MIP($)		MIP($)
Timesincefire	-0.009[a] (0.002)	-2,898	-0.005[a] (0.002)	-2,190	-0.004[b] (0.002)	-1,847	-0.01[a] (0.003)	-3,244
Ln(Size)	0.043[a] (0.009)	2.14	0.033[a] (0.009)	2.13	0.031[a] (0.009)	2.22	0.049[a] (0.014)	2.47
Hriskscore	-0.002[a] (0.001)	-692	-0.002[a] (0.0006)	-706	-0.002[a] (0.0006)	-778	-0.002[a] (0.0006)	-648
Spatial Coefficient[†]			0.223[a] (0.029)		0.291[a] (0.03)		0.443[a] (0.135)	
Adj. R sqr	0.78							
N	1,293							

Data = Assessed value
Past wildfire event/occurrence = the nearest fire burned in the last 7 years
Wildfire risk = House level risk
Functional form = Double-log

[a], [b] and [c] denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.
[†] If the preferred alternative is spatial lag model, then spatial correlation coefficient is rho. If it is spatial error model, then spatial correlation coefficient is lambda.

Table 6.17: Hedonic regression results (OLS) for model 2 with Composite risk (County)

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Constant	11.4***	11.4***	11.5***	11.3***
	(0.058)	(0.059)	(0.058)	(0.057)
Area	$2.4x10^{-4}$***	$2.4x10^{-4}$***	$2.5x10^{-4}$***	$2.4x10^{-4}$***
	($5.84x10^{-6}$)	($5.85x10^{-6}$)	($5.84x10^{-6}$)	($5.81x10^{-6}$)
Land	$2.4x10^{-8}$***	$2.4x10^{-8}$***	$2.4x10^{-8}$***	$2.4x10^{-8}$***
	($1.8x10^{-9}$)	($1.97x10^{-9}$)	($1.96x10^{-9}$)	($1.68x10^{-9}$)
Yr2004	0.012	0.006	0.007	0.03**
	(0.0132)	(0.0133)	(0.013)	(0.0128)
Yr2005	-0.032**	-0.038***	-0.035***	-0.013
	(0.0132)	(0.0134)	(0.013)	(0.0129)
Yr2006	-0.066***	-0.08***	-0.089***	-0.047***
	(0.013)	(0.014)	(0.014)	(0.013)
Yr2007	-0.086***	-0.1***	-0.11***	-0.067***
	(0.013)	(0.014)	(0.014)	(0.013)
Yr2008	-0.21***	-0.23***	-0.24***	-0.19***
	(0.014)	(0.014)	(0.015)	(0.015)
Yr2009	-0.23***	-0.25***	-0.26***	-0.21***
	(0.014)	(0.014)	(0.015)	(0.015)
Yr2010	-0.23***	-0.25***	-0.27***	-0.21***
	(0.014)	(0.015)	(0.015)	(0.015)
Yr2011	-0.23***	-0.24***	-0.26***	-0.21***
	(0.014)	(0.015)	(0.015)	(0.016)
Yr2012	-0.23***	-0.24***	-0.26***	-0.21***
	(0.013)	(0.014)	(0.014)	(0.014)
Yr2013	-0.23***	-0.24***	-0.25***	-0.2***
	(0.014)	(0.014)	(0.014)	(0.014)
Bedroom	0.018***	0.017***	0.017***	0.018***
	(0.004)	(0.004)	(0.004)	(0.004)
Bathroom	0.004	0.003	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Fireplace	0.069***	0.068***	0.067***	0.07***
	(0.006)	(0.006)	(0.006)	(0.006)
Aircond	0.013	0.011	0.01	0.014
	(0.01)	(0.01)	(0.01)	(0.01)
Evapcool	-0.023***	-0.023***	-0.026***	-0.021***
	(0.008)	(0.008)	(0.008)	(0.008)
Othercool	0.011	0.0086	0.0064	0.012
	(0.008)	(0.008)	(0.008)	(0.008)

Table 6.17: Hedonic regression results (OLS) for model 2 with Composite risk (County) (cont'd)

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Phycond	0.14***	0.13***	0.14***	0.14***
	(0.004)	(0.004)	(0.004)	(0.004)
Highsch	0.27***	0.28***	0.25***	0.26***
	(0.038)	(0.038)	(0.038)	(0.038)
Over65	0.5***	0.5***	0.54***	0.47***
	(0.052)	(0.052)	(0.052)	(0.052)
White	0.13*	0.052	0.062	0.17**
	(0.075)	(0.076)	(0.075)	(0.074)
Highway	0.007***	0.007***	0.006**	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
City	0.006**	0.004	0.003	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Lake	-0.015***	-0.015***	-0.015***	-0.016***
	(0.0007)	(0.0007)	(0.0007)	(0.0006)
Forest	-0.012***	-0.012***	-0.011***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)
Industry	0.003***	0.005***	0.007***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
WUI	0.048***	0.053***	0.05***	0.054***
	(0.01)	(0.01)	(0.01)	(0.01)
Firenum	-0.047***	-0.034***	-0.034***	-0.0027
	(0.01)	(0.006)	(0.004)	(0.003)
Avgsize	-2.6×10^{-7}	-4.3×10^{-6}***	-9.4×10^{-7}	3.2×10^{-7}
	(2.23×10^{-6})	(1.54×10^{-6})	(6.64×10^{-7})	(3.34×10^{-7})
Comp_high	0.021***	0.021***	0.024***	0.02***
	(0.006)	(0.006)	(0.006)	(0.006)
Comp_ext	0.044*	0.038	0.045*	0.043*
	(0.023)	(0.023)	(0.023)	(0.023)
Adj. *R* sqr	0.695	0.696	0.697	0.694
N	10,639			

Data = Estimated sale prices
Past wildfire event/occurrence = the aggregate fire burned in the last 7 years
Wildfire risk = Composite risk covering the County
Functional form = Semi-log

***, ** and * denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.18: Hedonic regression results (Spatial) for model 2 with Composite risk (County)

Variables	**Spatial error model with DIS0.5 weight matrix**			
	10km	**15km**	**20km**	**25km**
Constant	11.414*** (0.088)	11.45*** (0.088)	11.472*** (0.087)	11.41*** (0.088)
Area	2.3×10^{-4}*** (4.4×10^{-6})	2.3×10^{-4}*** (4.4×10^{-6})	2.3×10^{-4}*** (4.4×10^{-6})	2.3×10^{-4}*** (4.4×10^{-6})
Land	2.3×10^{-8}*** (3.6×10^{-9})	2.4×10^{-8}*** (3.6×10^{-9})	2.3×10^{-8}*** (3.6×10^{-9})	2.3×10^{-8}*** (3.6×10^{-9})
Yr2004	0.015 (0.013)	0.011 (0.013)	0.011 (0.013)	0.032*** (0.012)
Yr2005	-0.02 (0.013)	-0.025** (0.013)	-0.024* (0.012)	-0.003 (0.012)
Yr2006	-0.056*** (0.013)	-0.069*** (0.014)	-0.079*** (0.014)	-0.039*** (0.013)
Yr2007	-0.074*** (0.013)	-0.087*** (0.014)	-0.097*** (0.014)	-0.056*** (0.013)
Yr2008	-0.203*** (0.014)	-0.217*** (0.015)	-0.231*** (0.015)	-0.187*** (0.015)
Yr2009	-0.224*** (0.014)	-0.238*** (0.015)	-0.252*** (0.015)	-0.208*** (0.015)
Yr2010	-0.224*** (0.015)	-0.239*** (0.016)	-0.255*** (0.016)	-0.205*** (0.016)
Yr2011	-0.221*** (0.015)	-0.236*** (0.016)	-0.256*** (0.016)	-0.204*** (0.017)
Yr2012	-0.224*** (0.014)	-0.237*** (0.016)	-0.252*** (0.015)	-0.204*** (0.015)
Yr2013	-0.222*** (0.014)	-0.235*** (0.016)	-0.247*** (0.015)	-0.2*** (0.014)
Bedroom	0.018*** (0.004)	0.018*** (0.004)	0.017*** (0.004)	0.018*** (0.004)
Bathroom	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)
Fireplace	0.059*** (0.006)	0.059*** (0.006)	0.058*** (0.006)	0.059*** (0.006)
Aircond	0.017* (0.01)	0.016* (0.01)	0.016* (0.01)	0.017* (0.01)
Evapcool	-0.003 (0.008)	-0.003 (0.008)	-0.004 (0.008)	-0.002 (0.008)
Othercool	0.022*** (0.008)	0.022*** (0.008)	0.021*** (0.008)	0.023*** (0.008)

Table 6.18: Hedonic regression results (Spatial) for model 2 with Composite risk (County) (cont'd)

Variables	Spatial error model with DIS0.5 weight matrix			
	10km	**15km**	**20km**	**25km**
Phycond	0.126*** (0.004)	0.125*** (0.004)	0.127*** (0.004)	0.127*** (0.004)
Highsch	0.362*** (0.065)	0.359*** (0.064)	0.34*** (0.064)	0.35*** (0.065)
Over65	0.51*** (0.075)	0.491*** (0.074)	0.512*** (0.074)	0.494*** (0.076)
White	0.04 (0.109)	0.023 (0.109)	0.022 (0.107)	0.046 (0.109)
Highway	0.008** (0.004)	0.008** (0.004)	0.007* (0.004)	0.007* (0.004)
City	0.008** (0.004)	0.008* (0.004)	0.006 (0.004)	0.009** (0.004)
Lake	-0.015*** (0.001)	-0.015*** (0.001)	-0.015*** (0.001)	-0.016*** (0.001)
Forest	-0.013*** (0.002)	-0.014*** (0.002)	-0.013*** (0.002)	-0.013*** (0.002)
Industry	0.003 (0.002)	0.004** (0.002)	0.006*** (0.002)	0.003 (0.002)
WUI	0.059*** (0.015)	0.063*** (0.015)	0.062*** (0.014)	0.064*** (0.015)
Firenum	-0.043*** (0.01)	-0.031*** (0.007)	-0.031*** (0.005)	-0.003 (0.003)
Avgsize	$2.4\text{x}10^{-6}$ ($4.6\text{x}10^{-6}$)	$-7.\text{x}10^{-7}$ ($1.5\text{x}10^{-6}$)	$9.3\text{x}10^{-7}$ ($7.1\text{x}10^{-7}$)	$-9.4\text{x}10^{-8}$ ($3.9\text{x}10^{-7}$)
Comp_high	0.026*** (0.006)	0.027*** (0.006)	0.028*** (0.006)	0.026*** (0.006)
Comp_ext	0.025 (0.02)	0.024 (0.02)	0.028 (0.02)	0.026 (0.02)
Lambda	0.476*** (0.083)	0.468*** (0.085)	0.462*** (0.086)	0.479*** (0.083)
N	10,639			

Data = Estimated sale prices
Past wildfire event/occurrence = the aggregate fire burned in the last 7 years
Wildfire risk = Composite risk covering the County
Functional form = Semi-log

***, ** and * denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.19: Hedonic regression results (OLS) for model 2 with WUI risk

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Constant	11.5***	11.6***	11.6***	11.4***
	(0.15)	(0.15)	(0.16)	(0.15)
Area	2.1×10^{-4}***	2.1×10^{-4}***	2.1×10^{-4}***	2.1×10^{-4}***
	(1.1×10^{-5})	(1.1×10^{-5})	(1.1×10^{-5})	(1.1×10^{-5})
Land	9.2×10^{-8}*	9.3×10^{-8}**	9×10^{-8}*	7.3×10^{-8}
	(4.8×10^{-8})	(4.7×10^{-8})	(4.7×10^{-8})	(4.6×10^{-8})
Yr2004	-0.012	-0.034	-0.026	-0.013
	(0.027)	(0.028)	(0.028)	(0.028)
Yr2005	-0.058**	-0.08***	-0.069***	-0.058**
	(0.025)	(0.026)	(0.026)	(0.026)
Yr2006	-0.11***	-0.14***	-0.14***	-0.12***
	(0.027)	(0.028)	(0.029)	(0.029)
Yr2007	-0.11***	-0.14***	-0.14***	-0.12***
	(0.027)	(0.028)	(0.029)	(0.028)
Yr2008	-0.21***	-0.24***	-0.25***	-0.22***
	(0.028)	(0.03)	(0.031)	(0.031)
Yr2009	-0.23***	-0.26***	-0.27***	-0.24***
	(0.028)	(0.029)	(0.031)	(0.031)
Yr2010	-0.21***	-0.24***	-0.24***	-0.21***
	(0.028)	(0.03)	(0.032)	(0.033)
Yr2011	-0.23***	-0.27***	-0.27***	-0.24***
	(0.026)	(0.029)	(0.031)	(0.032)
Yr2012	-0.22***	-0.25***	-0.25***	-0.22***
	(0.025)	(0.027)	(0.029)	(0.031)
Yr2013	-0.21***	-0.24***	-0.24***	-0.21***
	(0.026)	(0.029)	(0.03)	(0.031)
Bedroom	0.005	0.004	0.005	0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Bathroom	0.011	0.011	0.011	0.011
	(0.008)	(0.008)	(0.008)	(0.008)
Fireplace	0.052***	0.049***	0.05***	0.052***
	(0.014)	(0.014)	(0.014)	(0.014)
Aircond	0.029	0.027	0.028	0.032
	(0.022)	(0.022)	(0.022)	(0.022)
Evapcool	-0.0002	-0.003	-0.004	-0.0008
	(0.017)	(0.017)	(0.017)	(0.017)
Othercool	0.026	0.023	0.02	0.026
	(0.018)	(0.018)	(0.018)	(0.018)

Table 6.19: Hedonic regression results (OLS) for model 2 with WUI risk (cont'd)

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Phycond	0.16***	0.16***	0.16***	0.16***
	(0.009)	(0.009)	(0.009)	(0.009)
Highsch	0.017	0.07	0.012	0.0024
	(0.16)	(0.16)	(0.16)	(0.16)
Over65	0.12	0.14	0.27*	0.19
	(0.15)	(0.15)	(0.16)	(0.16)
White	0.26**	0.12	0.13	0.28**
	(0.12)	(0.13)	(0.13)	(0.13)
Highway	0.009**	0.009**	0.007*	0.009**
	(0.003)	(0.003)	(0.004)	(0.004)
City	0.02***	0.018***	0.02***	0.022***
	(0.005)	(0.005)	(0.005)	(0.005)
Lake	-0.01***	-0.011***	-0.011***	-0.01***
	(0.001)	(0.001)	(0.001)	(0.001)
Forest	-0.008***	-0.01***	-0.007***	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Industry	0.008***	0.01***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Firenum	-0.081***	-0.045***	-0.025***	-0.006
	(0.022)	(0.01)	(0.007)	(0.006)
Avgsize	$4.7\text{x}10^{-6}$	$-3\text{x}10^{-6}$	$-1.5\text{x}10^{-6}$*	$-2.3\text{x}10^{-7}$
	($5.5\text{x}10^{-6}$)	($2.2\text{x}10^{-6}$)	($8\text{x}10^{-7}$)	($5.7\text{x}10^{-7}$)
WUI_high	0.001	0.004	0.008	-0.002
	(0.022)	(0.022)	(0.023)	(0.023)
WUI_vhigh	-0.07	-0.04	-0.045	-0.09**
	(0.044)	(0.044)	(0.046)	(0.044)
WUI_ext	0.0092	-0.026	0.016	0.017
	(0.054)	(0.054)	(0.054)	(0.054)
Adj. *R* sqr	0.678	0.679	0.678	0.676
N	2,529			

Data = Estimated sale prices
Past wildfire event/occurrence = the aggregate fire burned in the last 7 years
Wildfire risk = WUI risk
Functional form = Semi-log

***, ** and * denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.20: Hedonic regression results (Spatial) for model 2 with WUI risk

Variables	Spatial error model with DIS0.5 weight matrix			
	10km	**15km**	**20km**	**25km**
Constant	11.539*** (0.165)	11.666*** (0.169)	11.636*** (0.17)	11.509*** (0.171)
Area	$2x10^{-4}$*** ($8.0x10^{-6}$)	$2x10^{-4}$*** ($8.0x10^{-6}$)	$2x10^{-4}$*** ($8.0x10^{-6}$)	$2x10^{-4}$*** ($8.1x10^{-6}$)
Land	$9.4x10^{-8}$*** ($3.5x10^{-8}$)	$9.7x10^{-8}$*** ($3.4x10^{-8}$)	$9.2x10^{-8}$*** ($3.4x10^{-8}$)	$8.1x10^{-8}$** ($3.5x10^{-8}$)
Yr2004	-0.012 (0.028)	-0.033 (0.028)	-0.023 (0.028)	-0.011 (0.028)
Yr2005	-0.055** (0.025)	-0.076*** (0.026)	-0.065** (0.025)	-0.054** (0.025)
Yr2006	-0.111*** (0.026)	-0.138*** (0.027)	-0.135*** (0.027)	-0.113*** (0.028)
Yr2007	-0.115*** (0.026)	-0.144*** (0.027)	-0.142*** (0.027)	-0.119*** (0.028)
Yr2008	-0.21*** (0.028)	-0.24*** (0.029)	-0.242*** (0.031)	-0.218*** (0.032)
Yr2009	-0.229*** (0.029)	-0.26*** (0.03)	-0.262*** (0.031)	-0.234*** (0.033)
Yr2010	-0.209*** (0.03)	-0.242*** (0.031)	-0.24*** (0.033)	-0.21*** (0.035)
Yr2011	-0.237*** (0.028)	-0.273*** (0.03)	-0.272*** (0.032)	-0.24*** (0.036)
Yr2012	-0.218*** (0.028)	-0.249*** (0.029)	-0.25*** (0.031)	-0.217*** (0.035)
Yr2013	-0.213*** (0.028)	-0.244*** (0.029)	-0.242*** (0.031)	-0.211*** (0.033)
Bedroom	0.007 (0.007)	0.006 (0.007)	0.007 (0.007)	0.007 (0.007)
Bathroom	0.01 (0.007)	0.01 (0.007)	0.01 (0.007)	0.01 (0.007)
Fireplace	0.053*** (0.015)	0.051*** (0.015)	0.052*** (0.015)	0.053*** (0.015)
Aircond	0.019 (0.02)	0.017 (0.02)	0.019 (0.02)	0.02 (0.02)
Evapcool	-0.003 (0.017)	-0.005 (0.017)	-0.005 (0.017)	-0.004 (0.017)
Othercool	0.023 (0.017)	0.021 (0.017)	0.019 (0.017)	0.023 (0.017)

Table 6.20: Hedonic regression results (Spatial) for model 2 with WUI risk (cont'd)

Variables	**Spatial error model with DIS0.5 weight matrix**			
	10km	**15km**	**20km**	**25km**
Phycond	0.151*** (0.008)	0.151*** (0.008)	0.153*** (0.008)	0.154*** (0.008)
Highsch	0.084 (0.203)	0.117 (0.2)	0.063 (0.2)	0.067 (0.204)
Over65	0.19 (0.164)	0.189 (0.165)	0.312* (0.166)	0.268 (0.168)
White	0.171 (0.141)	0.065 (0.147)	0.086 (0.148)	0.17 (0.145)
Highway	0.009** (0.004)	0.009** (0.004)	0.008* (0.004)	0.01** (0.004)
City	0.021*** (0.006)	0.019*** (0.006)	0.021*** (0.006)	0.023*** (0.006)
Lake	-0.009*** (0.002)	-0.01*** (0.002)	-0.01*** (0.002)	-0.01*** (0.002)
Forest	-0.009*** (0.003)	-0.01*** (0.003)	-0.008*** (0.003)	-0.007** (0.003)
Industry	0.008*** (0.002)	0.009*** (0.002)	0.01*** (0.002)	0.01*** (0.003)
Firenum	-0.078*** (0.021)	-0.045*** (0.01)	-0.023*** (0.007)	-0.005 (0.006)
Avgsize	$6.6\text{x}10^{-6}$ ($6.6\text{x}10^{-6}$)	$-1.6\text{x}10^{-6}$ ($1.9\text{x}10^{-6}$)	$-7.4\text{x}10^{-7}$ ($9.4\text{x}10^{-7}$)	$-3.8\text{x}10^{-7}$ ($6.5\text{x}10^{-7}$)
WUI_high	-0.006 (0.026)	-0.004 (0.026)	$-2.2\text{x}10^{-4}$ (0.026)	-0.01 (0.027)
WUI_vhigh	-0.073 (0.045)	-0.044 (0.045)	-0.053 (0.046)	-0.095** (0.046)
WUI_ext	-0.003 (0.054)	-0.036 (0.054)	0.002 (0.053)	-0.002 (0.055)
Lambda	0.202* (0.118)	0.2* (0.119)	0.198* (0.119)	0.216* (0.117)
N	2,529			

Data = Estimated sale prices
Past wildfire event/occurrence = the aggregate fire burned in the last 7 years
Wildfire risk = WUI risk
Functional form = Semi-log

***, ** and * denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.21: Hedonic regression results (OLS) for model 2 with House level risk

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Constant	11.9^{***}	12.1^{***}	11.9^{***}	11.8^{***}
	(0.48)	(0.46)	(0.49)	(0.43)
Area	$1.7\text{x}10^{-4}$***	$1.7\text{x}10^{-4}$***	$1.7\text{x}10^{-4}$***	$1.8\text{x}10^{-4}$***
	$(2.5\text{x}10^{-5})$	$(2.5\text{x}10^{-5})$	$(2.5\text{x}10^{-5})$	$(2.4\text{x}10^{-5})$
Land	$1.3\text{x}10^{-7}$	$1.6\text{x}10^{-7}$	$1.3\text{x}10^{-7}$	$8.4\text{x}10^{-8}$
	$(1.3\text{x}10^{-7})$	$(1.2\text{x}10^{-7})$	$(1.3\text{x}10^{-7})$	$(1.3\text{x}10^{-7})$
Yr2004	0.065	0.067	0.082	0.065
	(0.086)	(0.085)	(0.083)	(0.084)
Yr2005	-0.10	-0.11	-0.085	-0.097
	(0.079)	(0.083)	(0.081)	(0.083)
Yr2006	-0.077	-0.090	-0.053	-0.099
	(0.086)	(0.087)	(0.088)	(0.094)
Yr2007	-0.18^{**}	-0.19^{**}	-0.17^{**}	-0.19^{**}
	(0.079)	(0.082)	(0.081)	(0.083)
Yr2008	-0.21^{**}	-0.23^{**}	-0.19^{*}	-0.17^{*}
	(0.090)	(0.095)	(0.098)	(0.10)
Yr2009	-0.093	-0.11	-0.078	-0.040
	(0.099)	(0.10)	(0.10)	(0.11)
Yr2010	-0.18^{*}	-0.23^{**}	-0.15	-0.11
	(0.095)	(0.11)	(0.11)	(0.12)
Yr2011	-0.25^{**}	-0.30^{***}	-0.21^{*}	-0.18
	(0.098)	(0.11)	(0.12)	(0.12)
Yr2012	-0.21^{**}	-0.26^{***}	-0.17	-0.18^{*}
	(0.088)	(0.100)	(0.11)	(0.10)
Yr2013	-0.18^{**}	-0.21^{**}	-0.13	-0.16
	(0.081)	(0.097)	(0.10)	(0.10)
Bedroom	0.019	0.018	0.016	0.015
	(0.023)	(0.023)	(0.023)	(0.022)
Bathroom	0.018	0.01	0.016	0.024
	(0.027)	(0.026)	(0.027)	(0.027)
Fireplace	0.073	0.082^{*}	0.073	0.074^{*}
	(0.045)	(0.044)	(0.045)	(0.044)
Aircond	0.043	0.048	0.041	0.047
	(0.068)	(0.068)	(0.066)	(0.070)
Evapcool	0.014	0.025	0.0068	0.0039
	(0.089)	(0.089)	(0.093)	(0.091)
Othercool	0.023	0.014	0.024	0.028
	(0.054)	(0.054)	(0.054)	(0.054)

Table 6.21: Hedonic regression results (OLS) for model 2 with House level risk (cont'd)

Variables	**No spatial OLS**			
	10km	**15km**	**20km**	**25km**
Phycond	0.13***	0.13***	0.13***	0.12***
	(0.026)	(0.027)	(0.027)	(0.028)
Highsch	-0.24	-0.32	-0.34	-0.25
	(0.49)	(0.49)	(0.49)	(0.48)
Over65	-0.16	-0.27	-0.055	-0.32
	(0.44)	(0.46)	(0.46)	(0.45)
White	0.16	0.22	0.25	0.23
	(0.49)	(0.51)	(0.50)	(0.46)
Highway	-0.007	-0.002	-0.008	-0.016
	(0.01)	(0.01)	(0.01)	(0.01)
City	0.032**	0.022	0.031*	0.025
	(0.016)	(0.015)	(0.018)	(0.015)
Lake	-0.014***	-0.017***	-0.017***	-0.013***
	(0.005)	(0.004)	(0.005)	(0.004)
Forest	0.0008	-0.0008	0.002	0.011
	(0.007)	(0.007)	(0.008)	(0.008)
Industry	0.017***	0.018***	0.019***	0.019***
	(0.005)	(0.004)	(0.005)	(0.005)
WUI	0.024	0.022	0.005	0.007
	(0.050)	(0.051)	(0.051)	(0.051)
Firenum	-0.066	-0.059**	-0.002	-0.003
	(0.04)	(0.025)	(0.025)	(0.021)
Avgsize	$2.4\text{x}10^{-7}$	$-1.3\text{x}10^{-5}$	$-2.5\text{x}10^{-5}$	$2.1\text{x}10^{-5}$***
	$(1.7\text{x}10^{-5})$	$(1.4\text{x}10^{-5})$	$(1.5\text{x}10^{-5})$	$(7.7\text{x}10^{-6})$
Hriskscore	$-1.2\text{x}10^{-4}$	$-3.5\text{x}10^{-4}$	$3.2\text{x}10^{-5}$	$2.5\text{x}10^{-4}$
	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R sqr	.645	.652	.643	.647
N	270			
Data = Estimated sale prices				
Past wildfire event/occurrence = the aggregate fire burned in the last 7 years				
Wildfire risk = House level risk				
Functional form = Semi-log				

***, ** and * denote significance at 1%, 5% and 10%, respectively. Standard Errors are in parentheses.

Table 6.22: Marginal implicit price estimates for model 2

Variables	Marginal implicit prices (in 2013 dollars)			
	10km	15km	20km	25km
Model 2 with Composite risk (County): No spatial OLS				
WUI	\$17,768	\$19,669	\$18,527	\$20,050
Firenum	-\$16,985	-\$12,287	-\$12,287	-\$976†
Avgsize	-\$0.09	-\$1.55	-\$0.34†	\$0.12†
Comp_high	\$7,669	\$7,669	\$8,777	\$7,300
Comp_ext	\$16,255	\$13,996†	\$16,633	\$15,877
Model 2 with Composite risk (County): Spatial error model with DIS0.5 weight matrix				
WUI	\$21,932	\$23,497	\$23,240	\$23,953
Firenum	-\$15,497	-\$11,346	-\$11,166	-\$1,216†
Avgsize	\$0.88†	-\$0.26†	\$0.34†	-\$0.03†
Comp_high	\$9,702	\$9,770	\$10,087	\$9,599
Comp_ext	\$9,131†	\$8,916†	\$10,082†	\$9,361†
Model 2 with WUI Risk: No spatial OLS				
Firenum	-\$36,559	-\$20,311	-\$11,284	-\$2,573†
Avgsize	\$2.12†	-\$1.35†	-\$0.68	-\$0.10†
WUI_high	\$451†	\$1,763†	\$3,807†	-\$767†
WUI_vhigh	-\$30,514†	-\$17,698†	-\$19,861†	-\$38,847
WUI_ext	\$4,171†	-\$11,584†	\$7,279†	\$7,738†
Model 2 with WUI risk: Spatial error model with DIS0.5 weight matrix				
Firenum	-\$35,412	-\$20,430	-\$10,510	-\$2,215†
Avgsize	\$3.02†	-\$0.73†	-\$0.33†	-\$0.17†
WUI_high	-\$2,779†	-\$1,868†	-\$101†	-\$4,545†
WUI_vhigh	-\$31,780†	-\$19,481†	-\$23,503†	-\$40,902
WUI_ext	-\$1,507†	-\$16,127†	\$1,061†	-\$1,008†
Model 2 with House level risk: No spatial OLS				
WUI	\$10,067†	\$9,219†	\$2,202†	\$2,744†
Firenum	-\$27,355†	-\$24,454	-\$705†	-\$1,327†
Avgsize	\$0.10†	-\$5.39†	-\$11†	\$8.70
Hriskscore	-\$50†	-\$146†	\$13†	\$103†

† The marginal implicit price is derived from insignificant coefficients.

Chapter 7 Summarizing hedonic model results: internal meta-analysis

This chapter comprehensively summarizes all 2,000 hedonic regression results using meta-analysis.

7.1 Introduction

This analysis exploits the hedonic model to examine the effect of wildfire on housing value, with varying data and econometric modeling techniques. Overall, the variation in the data and modeling techniques produces 2,000 results. For each model estimated, I save the features of the model, including R^2, data and econometric specification. I also save the sign and significance of the estimated wildfire variables together with the MIP estimates. I then use Krinsky Robb method to calculate 95% confidence intervals (and the standard error) for all MIP estimates (Krinsky & Robb, 1986).

Summarizing wildfire effects on property value, results show the expected negative effect of wildfire event/occurrence. Specifically, the mean estimate of the MIP for a one kilometer increase in the distance from the nearest fire is $3,461, implying an increase in assessed value of 1%. The mean estimate of the MIP for one additional burn near the house is $14,375, implying a decrease in assessed value of 5%. Nonetheless, the effect of wildfire risk ranges from a positive to an insignificant or a negative effect, depending on the measurement of fire risk, level of risk and geographic area.

Following Banzhaf and Smith (2007), I further investigate the variation in the MIP estimates via an internal meta-analysis approach using the results from these 2000 hedonic models as primary estimates. Specifically, I investigate what factors influence wildfire effects on property value. I conduct two meta-regressions, with the dependent variables being the MIP for a one kilometer increase in distance from the nearest fire and the MIP of one additional burn near the house, respectively. The explanatory variables are all dummy variables, capturing the features of hedonic model. They include a set of dummies indicating the measurement for data (i.e., measure for property value, wildfire event and risk) and a set of dummies indicating model specification (i.e., spatial model structure and associated weight matrices, and hedonic functional form). I run weighted least square on the meta-regression model, with the weights being the standard error of the observed MIP estimates.

Meta-analysis results show that models that use assessed value data not only give higher R^2 but also find more significant estimates and larger MIP estimates than models that use estimated sales prices data. However, the assessed value models do not necessarily yield estimates with smaller standard errors. Second, ignoring spatial autocorrelation either leads to overestimate of MIP or it has no significant effect on MIP estimates. Third, the measurement of wildfire risk significantly influences the effects of fire event/occurrence. This result reveals the importance of joint estimation of wildfire events and risks, and ignoring wildfire risks in hedonic models may yield inaccurate estimates.

7.2 What is meta-analysis?

Meta-analysis is a quantitative approach to synthesize the results on a particular topic in the literature, aiming to explain variation in the results obtained in different primary studies. Thus it requires a common empirical value in the primary studies, such as MIP estimate for a particular good or elasticity. Meta-analysis is the analysis of analyses (Glass, 1976). It provides a concise and structured way to integrate findings, as compared with the traditional narrative literature review. As a quantitative literature review, it usually employs a meta-regression to provide a statistical analysis of the variation in the results. Overview of primary studies is crucial to meta-analysis, and failure to collate all empirical evidence would result in bias in meta-analysis conclusion (Rothstein, Sutton, & Borenstein, 2006; Ahmed, Sutton, & Riley, 2012).

Nelson and Kennedy (2009) summarize several major objectives of meta-analysis. First, meta-analysis allows the investigator to draw pooled estimates of the underlying empirical value from primary studies, which is considered to be more reliable and accurate since it integrates findings in all relevant studies. Secondly, meta-analysis assesses the variation in the underlying empirical value. Primary studies may employ varying data, study design and model specification, and thus yield conflicting results. Meta-analysis investigates the variation in the results via meta-regression whose dependent variable is the underlying empirical value obtained in the primary study and whose independent variables are related to characteristics of the primary study, such as data employed and variables constructed, study design and hypothesis, and econometric models and techniques. Third, meta-analysis can also be used to predict within-sample and out-of-sample estimates of the dependent variable. Finally, a new application of meta-analysis is to summarize multiple results obtained in a single study/article, also called “internal” meta-analysis (Banzhaf & Smith, 2007; Kuminoff, Zhang, & Rudi, 2010; Klemick, Griffiths, Guignet, & Walsh, 2015).

Meta-analysis has been widely used to summarize the valuation measures obtained in environmental economics, such as endangered species (J. B. Loomis & White, 1996; L. Richardson & Loomis, 2009), environmental Kuznets Curve (Cavlovic, Baker, Berrens, & Gawande, 2000), pesticide risk (Florax, Travisi, & Nijkamp, 2005), environmental contamination (Simons & Saginor, 2006), railway station (Debrezion, Pels, & Rietveld, 2007), water quality (Van Houtven, Powers, & Pattanayak, 2007), open space (Brander & Koetse, 2011), renewable energy (C. Ma et al., 2015). Several meta-analysis studies particularly focus on welfare estimates obtained in hedonic property value models, such as air quality (Smith & Huang, 1995), noise damage (Schipper, Nijkamp, & Rietveld, 1998; Nelson, 2004), waste site (Braden, Feng, & Won, 2011).

7.2.1 Internal Meta-analysis

Meta-analysis summarizes the results across a set of studies. For example, Cavlovic et al. (2000) used 25 studies on the estimation of environmental Kuznets Curve, which yield 121 observations for meta-analysis. In recent years, researchers apply this approach in the context of a single study and summarize the results estimated from a particular study. When applied in a single study context, meta-analysis was designated as internal meta-analysis (Kuminoff et al., 2010). One can see that the difference between the standard and the internal meta-analysis lies in the source of data: the data used in internal meta-analysis are obtained from a single study while the data for the standard meta-analysis are usually obtained from multiple studies.

Kuminoff et al. (2010) explained the procedure of an internal meta-analysis. The first step requires one to specify a set of models that systematically vary along multiple dimensions (e.g., measurements for key variables, model specifications and econometric techniques). The choices researchers made along these dimensions and their possible combinations can lead to a huge number of models. The second step is to estimate all models or a random subset (when the number of models is overwhelmingly large).

Typically, the models contain a common economic value (e.g., marginal WTP estimates). For each model estimated, one saves its economic value and features of the model in which model attributes include the choices researchers made along different dimensions. The third step is to regress economic values against model attributes. This allows one to explore what influences researchers' choices have on the economic value obtained via the second step.

The first internal meta-analysis examining the effect of choices and assumptions made by researchers is by Banzhaf and Smith (2007). They estimated households' WTP for improved air quality based on home buyers' behavior in the housing market. This requires the researchers to specify alternative houses that buyers considered, or the choice set. They made assumptions about choice sets along three dimensions: spatial boundary, budget boundary and time boundary. Spatial boundary refers to the area that buyers consider when purchasing a house. Two potential spatial boundaries are defined: the actual county of residence or the entire area. Budget boundary defines the price range that buyers search. They defined four high-end budget constraints; a household would consider houses whose annualized price is less than or equal to 100%, 63%, 52% or 44% of annual income. They also defined four low-end budget constraints: house annualized price greater than or equal to 0%, 10%, 14% or 17% of annual income. The time window defines how long buyers and houses would stay in the market. Specifically they considered four time windows: 1, 2.5, 3 and 7 months. Overall variations in spatial, budget and temporal boundaries yield 128 potential choice sets. After defining choice sets, they further estimated households' willingness to pay for air quality improvement using discrete choice model. Finally, they exploited meta-regression to explain how assumptions about choice sets affect welfare estimates, with the dependent variable being WTP for air quality improvement and the independent variables being indicator variables for the boundaries in each dimension. They found choice set boundaries have significant effects.

Later, Kuminoff et al. (2010) used internal meta-analysis to investigate the sensitivity of welfare estimates derived from hedonic models to econometric modelling decisions, including functional form and the choices of covariates. In their study, they first employed hedonic model to examine the premium WTP for green hotels. They utilized two functional forms: linear and log-linear. They also considered different combination of covariates in the hedonic model (e.g., number of floors, whether the hotel provide free breakfast or free internet), up to 24 potential covariates. Two potential functional forms and 24 potential covariates yield more than 33 million hedonic models. They randomly select 40,000 specifications to estimate customers premium WTP for green hotels. Subsequently, they performed a meta-analysis of how decisions about functional form and covariates affect welfare estimates, with the dependent variables being premium WTP and the independent variables being indicator variables for functional form and whether each covariable is included in the hedonic model. They found that the price premium is quite robust to hedonic functional form as well as the choices of covariates.

Walsh, Griffiths, Guignet, and Klemick (2017) conducted a series of hedonic models to systematically investigate the effect of water clarity on housing value. Systematic investigation includes varying functional forms (semi-log and double-log), geographic areas (14 counties) and variable constructed (5 measures for proximity to

Chesapeake Bay and 2 measures of water clarity). Combination of the choices made along these dimensions yield 280 estimated hedonic model results. Using results from Walsh et al., analysis, Klemick et al. (2015) utilized meta-analysis to explain the variation in the elasticity of water clarity. The dependent variable in meta-analysis is elasticity of water charity derived from hedonic models, and the independent variables include indicator variables for functional forms, measures of water clarity, etc.

7.3 Meta-analysis: theoretical background

7.3.1 Methodological issues

Similar to meta-analysis, internal meta-analysis also faces several major methodological issues, as outlined by Nelson and Kennedy (2009). These estimation issues include dependent or correlated effect sizes, heterogeneity among effect sizes and heteroskedasticity associated with effect size variance.

7.3.1.1 Correlated effect sizes

Meta-analysis assumes effect size estimates obtained from the primary studies are independent. However, dependent or correlated effect sizes are very common in empirical research. Dependency can arise for a variety of reasons. Two types of dependencies are categorized in meta-analysis: correlated effects and hierarchical effects (Tipton, 2013; Tanner-Smith & Tipton, 2014). Correlated effects can occur when multiple observations are derived from the same participant (e.g., alcohol consumption at 6 month and 12 month post-intervention) or multiple treatments are contrasted with a single control group. Hierarchical effects occur when effect sizes are nested within clusters. For example, a study might provide multiple estimates or several studies use the same functional form. These two types of dependency can both exist within a single meta-analysis. Failure to account for dependence can result in biased standard error and more weight given to studies providing more effect sizes (Scammacca, Roberts, & Stuebing, 2014).

To address dependent estimates, several approaches have been used in the literature. First, the analyst only uses one estimate from each study (Mark & Wilson, 2001; Rose & Stanley, 2005). For example, the analyst might randomly choose one estimate or he might use the mean or median estimate from each study. Thus there is great loss of information associated with this approach. Besides, there is little theoretical guidance about how to select the estimate. Secondly, the analyst includes dummy variables (fix effects) for studies providing multiple estimates or studies utilizing the same functional form. The analyst can also employ a multivariate meta-analysis (Olkin & Gleser, 2009). However this approach requires information about dependence structure of effect size or the underlying data, and thus it is not commonly used in the literature (Riley, 2009).

7.3.1.2 Heterogeneous effect size variance

When pooling estimates from multiple studies, it is common that some studies provide more precise estimates. That is, effect size estimates have heterogeneous variance. These studies carry more accurate estimates, and thus should be given more weights. To account for heterogeneity, the meta-analyst usually calculates the weighted mean of effect sizes or performs weighted regression models, in which each observation is weighted using the inverse of the variance or standard error of effect size (Cipollina & Salvatici, 2010; Klemick et al., 2015). In most cases, effect size variance are not reported in primary studies. Instead, the meta-analyst usually uses sample size of the primary study as weights (Florax et al., 2005; Van Houtven et al., 2007). However effect size variance are generally available in internal meta-analysis since it is typical that the same author conducts both primary studies and the following meta-analysis.

7.3.1.3 Within-study and between-study variance

Deriving the summary effect size requires the meta-analyst to make assumptions about the population effect size. In empirical analysis, different assumptions lead to two different meta-analysis models: fixed-effects model and random-effects model (Brockwell & Gordon, 2001).[17] Fixed effect model assumes that there is one true population effect size shared by all studies, and thus variation in the observed effect is simply due to random sampling error (also called within-study variance). However random-effects model assumes that the population effect sizes vary across studies, generally following normal distribution, and the observed estimates are a random sample from a distribution of all possible population effect sizes. Thus random-effects models assumes variation in effect sizes is influenced by multiple characteristics of primary studies, including sample, study design, model specification, and so on. Therefore, the observed variation in effect sizes reflect both within-study variance and between-study variance.

The weighted means of the observed effect size for k studies is calculated as

$$\overline{\gamma} = \frac{\sum_{i=1}^{k} w_i \gamma_i}{\sum_{i=1}^{k} w_i} \tag{7.1}$$

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[17] In this analysis, the terms, fixed-effects and random-effects models are specific to models used in meta-analysis, which are different from models used in panel data analysis.

where γ_i is the observed effect size in study i, W_i is the weights for study i. Using the variance of the observed effect size as the weights (Higgins & Thompson, 2002), then

$w_i = \frac{1}{Se(\gamma_i)^2}$ for fixed-effects model

$w_i = \frac{1}{Se(\gamma_i)^2 + \hat{\tau}^2}$ for random-effects model

where $\hat{\tau}^2$ is the between-study variance. Standard error for $\overline{\gamma}$ is

$$\mathrm{Se}(\overline{\gamma}) = \frac{1}{\sqrt{\sum_{i=1}^{k} w_i}} \tag{7.2}$$

Compared to weights in fixed-effects models, incorporating between-study variance results in smaller weights for studies with more precise estimates while larger weights for studies with less precise estimates. Random-effects models also lead to more conservative estimates because of larger standard error and confidence intervals for the weighted mean estimates. Three statistics have been used in the literature to test effect size homogeneity. The I^2index, which would report the percentage of heterogeneity attributable to between-study variance, is used in this analysis (Huedo-Medina, Sánchez-Meca, Marín-Martínez, & Botella, 2006). Following Higgins and Thompson (2002), I use I^2 value of 25, 50 and 75 to indicate low, moderate and high heterogeneity, respectively. For example, I^2 value of 0 means all heterogeneity among effect size estimates are due to random sampling error; I^2 value of 25 means 25% of heterogeneity are due to the true heterogeneity between study, or between-study variance).

7.3.2 Meta-regression

A standard meta regression model typically includes a set of moderator variables to explain heterogeneity in the observed effects, expressed as

$$\gamma_i = a + \beta * Z_i + \varepsilon_i \quad (7.3)$$

where Z_i is a set of explanatory variables capturing characteristics of study i, including sample, study design, model specification and so on. γ_i is the same as defined in (7.1). The regression model in internal meta-analysis is similar to the standard meta-analysis with one exception. In internal meta-analysis, one summarizes effect size estimates obtained from a set of models instead of a set of studies. Therefore, γ_i denotes the observed effect in model i and Z_i is a set of explanatory variables capturing characteristics of model i.

As explained earlier, the error term in meta-regression ε_i might be heterogeneous. The meta-analyst generally conducts weighted regression models, with the weights measuring the precise of the observed effect (Cavlovic et al., 2000; Cipollina & Salvatici, 2010; Braden et al., 2011; Soon & Ahmad, 2015). Following Higgins and Thompson (2002), I divide (7.3) by the standard error of the observed effect and estimate meta-regression model using weighted least squares:

$$\frac{\gamma_i}{Se(\gamma_i)} = a + \beta * \frac{Z_i}{Se(\gamma_i)} + \varepsilon_i \quad (7.4)$$

The analyst also needs to take into account dependent effect size (e.g., multiple estimates from one study or one dataset). The common practice is to cluster at the study level or the sample level to get cluster-robust standard errors. In addition, the analyst needs to employ random-effects model to take into account between-study variance. In this analysis, both clustering and random-effects are handled since I include a full set of dummy variables (fixed effects) representing all characteristics of hedonic models. Thus the meta-regression model is estimated with weighted lease squares method.

7.3.2.1 Dependent variables

I conduct two meta-regressions. The dependent variable in the first meta-regression is the MIP for a one kilometer increase in distance from the nearest fire (*Dist*). The dependent variable in the second meta-regression is the MIP of one additional burn near the house (*Firenum*).

7.3.2.2 Explanatory variables

The explanatory variables in meta-regression are all dummy variables, which capture the characteristics of hedonic model. All explanatory variables are defined in Table 7.1. Overall, model features can be categorized into two groups: data and econometric specification. More specifically, I include dummy variables to indicate data source for housing prices (assessed value or estimated sales prices), data for past wildfire event/occurrence (fires burned in the last 7 years or fires burned in the last 15 years, 10km, 15km, 20km and 25km radius buffer zone), measurement of wildfire risk (composite risk, WUI risk or house level risk). For econometric specification, I include dummy variables for hedonic functional form (semi-log or double-log) and spatial dependency structure and weight matrices.

7.4 Descriptive statistics of wildfire effects

Of 2,000 estimated hedonic models, 200 models are estimated using OLS method. The adjusted R-squared of OLS models range from 0.66 to 0.82, with an average of 0.73.[18] This indicates that OLS models have good measures-of-fit. More specifically, the

[18] No R-squared or adjusted R-squared is obtained for spatial autoregressive models since these models use the generalized methods of moments based on instrumental variables.

t-test shows the average adjusted R-squared for assessed value models (0.77) are significantly higher than that in estimated sales price models (0.68). This finding is consistent with previous studies (Schuler, 1990; Kim & Goldsmith, 2005; Grimes & Aitken, 2008, Ma &Swinton, 2012).

7.4.1 Descriptive statistics of the sign

To investigate the direction of wildfire effects, I categorize the sign of estimated coefficients on wildfire variables into three categories: positively significant, negatively significant, or insignificant, where the cut-off level of significance is 10%.[19] Table 7.2 reports the direction of wildfire effects. The big two conclusions are as follows. First, past wildfire event/occurrence have a negative effect on property value. Secondly, the effects of wildfire risks are mixed, depending on risk measure, risk level and geographic area.

For effects on wildfire events on property values, we focus on the direction of two variables: *Dist* and *Firenum*. First, the vast majority of the models (72%) find the expected positive effect of *Dist*. 18% of models find nonsignificant relation, and the remaining 10% produce a significantly negative one. [20] Thus proximity to nearest wildfire reduces property values. Secondly, 71% of hedonic models report significantly negative coefficients on *Firenum*, while 25% of the models find no significant relationship. Thus frequent wildfires also lower property value. However, only 20% of the models find the

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[19] All significance levels are based on two-tail tests.

[20] Of 40 models generating the negative estimates of *Dist*, 30 models utilized composite risk data covering the Non-WUI area.

negative effects of *Firenum* decrease with the radius of buffer zone increase. Overall, past wildfire events/occurrence have a negative effect on property values. This finding is consistent with earlier studies on the effects of past wildfire events/occurrence (J. Loomis, 2004; J. Mueller et al., 2009; Stetler et al., 2010).

The effects of wildfire risk vary by risk level. Specifically, 66% of models report significantly positive coefficients on *Comp_high* while 73% of models report nonsignificant positive coefficients on *Comp_ext*. A similar pattern is detected for the effects of WUI risk. 51% of 400 models find significantly positive coefficients on *WUI_high*; 43% of models find significantly negative coefficients on *WUI_vhigh*, and 57% were not significant; 67% of models find nonsignificant coefficient on *WUI_ext*. This finding shows wildfire risk increases property values below a certain risk level and the relationship tends to be negative or insignificant once risk reaches a certain level. In addition, the estimated coefficient on house level risk is found to be significantly negative in 46% of models, while 54% didn't find a significant effect. Thus the effect of wildfire risk vary by risk level as well as risk measure.

In addition, the effects of wildfire risk vary by geographic area. Table 7.3 report the sign of estimated coefficients on composite risk in the WUI models and Non-WUI models. In the Non-WUI models, 40% of the models find significantly positive coefficients for both *Comp_high* and *Comp_ext*; 60% of the models find significantly positive coefficient for Comp*_high* and nonsignificant coefficient for *Comp_ext*. In the WUI models, 77% of models find both nonsignificant estimates and 19% find at least one negatively significant estimate. Thus the positive effect of amenity dominates in the Non-WUI whereas the relationship becomes insignificant or negative in the WUI. It is consistent with our hypothesis that the effect of wildfire risk differs across geographic areas. Overall, the effect of wildfire risk is mixed, depending on risk measure, risk level and geographic area. This finding further confirms Donovan et al.'s arguments about the complexity of risk effects: wildfire risk and amenity values are confounded in the risk assessment and they have opposite effects on property values.

7.4.2 Comparing the direction of wildfire event effects across alternative models

I then compare the sign of the estimated coefficients on *Dist* and *Firenum* across alternative models via Pearson's chi-square test (Table 7.4). The test statistics indicate there is significant difference in the distribution of signs across models that use assessed value data and models that use estimated sales price. The assessed value models are more likely to find the negative effects of wildfire events on property values (more significant positive estimates for *Dist* and more significantly negative estimates for *Firenum*). This finding is consistent with arguments in Kim and Goldsmith's study that assessed value data is superior to sale prices data in terms of revealing environmental effects on property values, especially when the size of sale prices data is significantly reduced due to poor data quality or slow sales. However little difference exists across OLS models and spatial autoregressive models.

7.4.3 The simple statistics of MIP estimates

This section summarizes the magnitude of wildfire effects. The MIP estimates are calculated using the average housing value and the average level of the independent variable for the sample population (Table 6.11). I then divide MIP estimates by the average assessed value $318,934 (expressed as a percentage change in assessed value) to give a better understanding of wildfire effects on property value. All MIP estimates are measured in 2013 dollars. Table 7.5 presents the simple statistics of estimates, which does not take into account statistical significance and variance of the observed estimate. Generally, the observed estimates range from negative values to positive values, implying the existence of negative marginal WTP estimates. F test results reject the null hypothesis that the average of estimates is equal to 0.

On average, the mean estimate of MIP_{Dist}, the MIP for a one kilometer increase in distance from the nearest fire (*Dist*), is $3,553 (in 2013 dollars), implying an increase in assessed value of 1.1%. The mean estimate of $MIP_{Firenum}$, the MIP for one additional fire near the house (*Firenum*), is $20,151 (in 2013 dollars), implying a decrease in assessed value of 6.4%. Further, houses located in zones with higher risk rating have higher values, except for houses located in the very high WUI risk zone. For example, the mean estimate of MIP_{Comp_high}, the MIP for living in high composite risk zone (*Comp_high*), is $6,065 (in 2013 dollars); the mean estimate of MIP_{Comp_ext}, the MIP for living in extreme composite risk zone (*Comp_ext*), is $10,472. Overall, the increase in property value varies from $6,065 to $18,013, indicating 1.9% and 5.7% of assessed value, respectively. However, if risk is measured at individual house level, the mean estimate of $MIP_{Hriskscore}$, the MIP for a one point increase in house risk score (*Hriskscore*), is $383 (in 2013 dollars), which represents a 0.1% drop in assessed value.

I then compare the distribution of the observed effects across alternative models to see if there are distinctive patterns across models that use different data or model specifications. I focus on two estimates: MIP_{Dist} and $MIP_{Firenum}$. Figure 7.1 to Figure 7.5 provide the kernel density estimate of MIP_{Dist} across alternative models. First, the distribution of MIP_{Dist} estimates is lopsided, with the majority report positive MIP_{Dist}. This is consistent with the hypothesis that proximity to near fire reduces house value. Secondly, KS test results indicate there is significant difference in the distribution of MIP_{Dist} estimates between models that use assessed value and models that use sales prices, or models that use 7-year time window and models that use 15-year time window, or models that covering the Non-WUI area and models that covering the WUI area, or models that different hedonic functional form. However little significant difference exists between OLS models and spatial autoregressive models. Figure 7.6 to 7.10 provides the kernel density estimate of $MIP_{Firenum}$ across alternative models. Similarly, there is significant difference in the distribution of $MIP_{Firenum}$ estimates with two exceptions. Little difference is found across the semi-log models and the double-log models, or OLS models and spatial autoregressive models.

7.4.4 Meta-analytic summary statistics of MIP estimates

As explained earlier, meta-analytic summary statistics is different from the simple summary statistics in that each observed effect size is weighted based on its associated statistical significance and variance. Specifically, in fixed-effects model, the weights are variance of the observed effect while in random-effects model the weights also take into account between-study variance. Thus the fixed-effects model is a special case of the random-effects model. In empirical analysis, the random-effects model is more commonly used since the assumption of a common effect size in fixed-effects model seems unrealistic. Moreover, the I^2 index shows that a large proportion of heterogeneity between the observed effect are attributable to between-study variance. Therefore, I focus on estimates derived in the random-effects model.

Table 7.6 presents the meta-analytic average of MIP estimates and 95% confidence intervals. The null hypothesis of no effect is highly rejected. The pooled estimates in random-effects model are somewhat different from the simple summary statistics. The pooled effects of wildfire events are smaller in random-effects models while the effects of wildfire risk are larger in random-effects models. For example, the pooled MIP_{Dist} estimate is $3,461[95% CI: $3,188, $3,734], indicating 1.1% of assessed value; the pooled $MIP_{Firenum}$ estimate is $14,375 [95% CI: $13,821, $14,928], representing 4.6% of assessed value.

Huggett Jr et al. (2008) find that sale prices increase approximately $48 per kilometer farther away from the closet fire, representing a 0.04% increase in sale prices. Generally MIP_{Dist} estimates in this analysis are slightly higher than their estimates. Xu and van Kooten (2013) find that the number of fires does not significantly affects sale prices while it has a significant effect on unit price (price per square meter). One extra burn within 5km radius would reduce unit price by $3.93, representing 0.8% of unit price. $MIP_{Firenum}$ estimates in this analysis are higher than their estimates.

Overall, our MIP estimates are in the lower end of the range of estimates reported in earlier wildfire studies. J. M. Mueller and Loomis (2010) find price drop caused by fires is about 5%. Hansen and Naughton (2013) find a 5.5% decrease for small size fires burned within 0.1 kilometer. The Cerro Grande fire caused price drop ranging from 3% to 11%. Stetler et al. (2010) find prices drop caused by wildfire event varies from 7.6% to 13.3%. Loomis (2004) find fire burned nearby decreases the price by approximately 15%. J. Mueller et al. (2009) report the first fire burned would decrease house price by 10% and the second fire would further decrease price by 23%.

7.4.5 Comparison of the standard error of MIP estimates across alternative models

I also compare the standard error of MIP estimates via Kolmogorov-Smirnov (KS) test, a statistic comparing distribution across two samples(Table 7.7). I reject the null hypothesis of identical distribution across OLS and spatial autoregressive models. One observes that OLS models are more likely to produce precise MIP estimates than spatial autoregressive models. That is, the standard errors of MIP are relatively smaller in OLS models. However there is no consistent pattern across models that use different data or functional form. For example, the assessed value models produce smaller standard errors of MIP_{Dist} but larger standard errors of $MIP_{Firenum}$.

7.5 Meta-regression results

Table 7.8 report meta-regression results. The dependent variable in the first column is MIP_{Dist} and the dependent variable in the second column is $MIP_{Firenum}$. Both models show a good fit, with the R^2 value of 0.68 and 0.7, respectively. This implies that characteristics of hedonic models can explain about 70% of variation in the MIP estimates. Overall, the estimated coefficients in the meta-analysis are statistically significant, indicating that data and econometric modeling techniques significantly influence MIP estimates.

First, the dummy variable for whether the model used assessed value data are positive and significant at 1% levels in both models. This shows models that use assessed value data are more likely to yield larger MIP estimates relative to models that use estimated sale prices data. J. Kim and Goldsmith (2009) find the superiority of assessed value data over sales price data due to significantly reduced data size and spatial abnormality of properties. This meta-analysis results confirm that assessed values are more likely to reveal environmental effects on property values when there is slow sales where the size of sale prices data is relatively small.

Secondly, the dummy variables for risk measurements are significant at 1% level, suggesting the measurements for risk have significant effects on the estimates of wildfire event/occurrence. Moreover, the magnitude of these coefficients are relatively large, meaning that the measurement for risk is the most important factor that influences wildfire events effects on property value. Therefore, previous studies investigating the effects of wildfire events but didn't take into account wildfire risk may lead to inappropriate estimates.

Third, the effects of time frame is mixed. Using fires burned in the last 7 years would yield larger $MIP_{Firenum}$ estimates than using fires burned in the last 15 years but it has no significant effect on MIP_{Dist}. The estimated coefficients on radius of buffer zones are negative and significant at 1%, suggesting that fires burned near the house (within 10km buffer zone) reduce property value more than fires burned farther away. However, MIP estimates increases with the increase in buffer zone, which is contrary to our expectation.

There is no consistent pattern in the effect of functional form. The semi-log models find larger MIP_{Dist} while smaller $MIP_{Firenum}$, compared to the double-log models. The estimated coefficients on spatial dependency are either insignificant or significantly negative, indicating that there is no significant difference in MIP estimates across OLS models and spatial autoregressive models or OLS models yield larger MIP estimates.[21] J. M. Mueller and Loomis (2008) find that little difference exist in MIP estimates between OLS models and spatial correlated models. The meta-analysis results partially confirm their findings. J. Kim and Goldsmith (2009) find that OLS models tend to overestimate the impact of swine production on property values. Their finding is also consistent with the meta-analysis results that OLS models are more likely to report overestimates of MIP.

[21] There are two exceptions. Spatial autoregressive models yield larger $MIP_{Firenum}$ estimates than OLS model: the first case is spatial lag model with four nearest neighbor weight matrix and the second case is general spatial model with the distance inverse weight matrix.

Table 7.1: Variable descriptions, descriptive statistics in meta-regression

Variable[a]	Definition	Mean (Std. Dev)
Data		
Assessed value	=1 if the hedonic model uses assessed value data	0.5 (0.5)
7-yr time window	=1 if the hedonic model uses fires burned in the last 7 years	0.5 (0.5)
15km radius[b]	=1 if the hedonic model uses 15km radius buffer zone	0.25 (0.43)
20km radius[b]	=1 if the hedonic model uses 20km radius buffer zone	0.25 (0.43)
25km radius[b]	=1 if the hedonic model uses 25km radius buffer zone	0.25 (0.43)
Composite risk (County)	=1 if the hedonic model uses composite risk data, which covers the Santa Fe County	0.2 (0.4)
Composite risk (WUI area)	=1 if the hedonic model uses composite risk data, which covers the WUI area	0.2 (0.4)
WUI risk	=1 if the hedonic model uses WUI risk data	0.2 (0.4)
House risk	=1 if the hedonic model uses house level risk data	0.2 (0.4)
Econometric specification		
Semi-log	=1 if the hedonic model uses semi-log functional form	0.5 (0.5)
Lag, WM=Knn4	=1 if the hedonic model is spatial lag model with Knn4 weight matrix	0.1 (0.3)
Lag, WM=Knn8	=1 if the hedonic model is spatial lag model with Knn8 weight matrix	0.1 (0.3)
Lag, WM=Distance inverse	=1 if the hedonic model is spatial lag model with the distance inverse weight matrix	0.1 (0.3)
Error, WM=Knn4	=1 if the hedonic model is spatial error model with Knn4 weight matrix	0.1 (0.3)
Error, WM=Knn8	=1 if the hedonic model is spatial error model with Knn8 weight matrix	0.1 (0.3)
Error, WM=Distance inverse	=1 if the hedonic model is spatial error model with the distance inverse weight matrix	0.1 (0.3)
General, WM=Knn4	=1 if the hedonic model is general spatial model with Knn4 weight matrix	0.1 (0.3)
General, WM=Knn8	=1 if the hedonic model is general spatial model with Knn8 weight matrix	0.1 (0.3)
General, WM=Distance inverse	=1 if the hedonic model is general spatial model with the distance inverse weight matrix	0.1 (0.3)

[a] The omitted case is the hedonic model that use estimated sale prices data, or 15-year time window, or 10km radius buffer zone, or composite risk covering the Non-WUI area, or double-log functional form, or OLS model.

[b] The variable is only included in the meta-regression if the dependent variable is the marginal implicit price for one additional fire near the house.

Table 7.2: Direction of wildfire effects on property values

Variable	**Significantly[a] Positive**	**Significantly[a] negative**	**Insignificant**	**# of estimates**
Wildfire event				
Dist	289 (72.25%)	40 (10%)	71 (17.75%)	400
Firenum	62 (3.88%)	1,132 (70.75%)	406 (25.38%)	1,600
Wildfire risk				
Comp_high	792 (66%)	71 (5.92%)	337 (28.08%)	1,200
Comp_ext	318 (26.5%)	8 (0.67%)	874 (72.83%)	1,200
WUI_high	204 (51%)	-	196 (49%)	400
WUI_vhigh	3 (0.75%)	170 (42.5%)	227 (56.75%)	400
WUI_ext	134 (33.5%)	-	266 (66.5%)	400
Hriskscore	-	182 (45.5%)	218 (54.5%)	400

[a] The cutoff level of significance is 10%, based on two-tail tests.

Table 7.3: Direction of composite risk on property values in the Non-WUI area vs the WUI area

Model	Sign[a]		Frequency (percentage)
	Comp_high	**Comp_ext**	
Model using Composite risk (Non-WUI area)	Positive	Insignificant	242 (60.5%)
	Positive	Positive	158 (39.5%)
Model using Composite risk (WUI area)	Insignificant	Insignificant	309 (77.25%)
	Negative	Insignificant	69 (17.25%)
	Positive	Insignificant	9 (2.25%)
	Insignificant	Negative	6 (1.5%)
	Insignificant	Positive	3 (0.75%)
	Positive	Positive	2 (0.5%)
	Negative	Negative	2 (0.5%)

[a] The cutoff level of significance is 10%, based on two-tail tests.

Table 7.4: Pearson's chi-square test results of the sign of the estimated coefficient on Dist and Firenum

Model Characteristics	**Dist[a]**			**Firenum[a]**		
	Insignificant	**Positive**	**Negative**	**Insignificant**	**Positive**	**Negative**
Data for housing prices						
Assessed value	7%	88%	5%	13.75%	4.88%	81.38%
Estimated sale price	28.50%	56.50%	15%	37%	2.88%	60.12%
Chi-square test	Reject the null hypothesis of identical distribution					
Functional form						
Semi-log	19.50%	68.50%	12%	27.88%	3.75%	68.38%
Double-log	16%	76%	8%	22.88%	4%	73.13%
Chi-square test	Fail to reject the null hypothesis			Reject the null hypothesis of identical distribution at 10% level		
Spatial dependency structure and weight matrices						
OLS	15%	72.50%	12.50%	20%	3.75%	76.25%
Lag, WM=Knn4	17.50%	72.50%	10%	25.62%	3.75%	70.63%
Lag, WM=Knn8	25%	67.50%	7.50%	25.62%	5%	69.38%
Lag, WM=Distance inverse	15%	72.50%	12.50%	18.13%	3.75%	78.13%
Error, WM=Knn4	12.50%	75%	12.50%	22.50%	3.13%	74.38%
Error, WM=Knn8	12.50%	75%	12.50%	23.13%	3.13%	73.75%
Error, WM=Distance inverse	22.50%	70%	7.50%	31.87%	2.50%	65.63%
General, WM=Distance inverse	20%	72.50%	7.50%	32.50%	3.13%	64.38%
General, WM=Knn4	17.50%	72.50%	10%	25.62%	5%	69.38%
General, WM=Knn8	20%	72.50%	7.50%	28.75%	5.63%	65.63%
Chi-square test	Fail to reject the null hypothesis of identical distribution					

[a] The cutoff level of significance is 10%, based on two-tail tests.

Table 7.5: Descriptive statistics of MIP estimates[a]

MIP estimate	Mean	Min	Max	% change in assessed value (based on mean estimates)	# of estimates
Wildfire event					
MIP_{Dist}	\$3,553	-\$9,024	\$19,141	1.1%	400
$MIP_{Firenum}$[b]	\$20,151	-\$283,306	\$280,768	6.4%	1,600
Wildfire risk					
MIP_{Comp_high}	\$6,065	-\$15,908	\$28,054	1.9%	1,200
MIP_{Comp_ext}	\$10,472	-\$20,872	\$45,324	3.3%	1,200
MIP_{WUI_high}	\$18,013	-\$10,126	\$49,623	5.7%	400
MIP_{WUI_vhigh}	-\$20,810	-\$72,205	\$19,234	-6.6%	400
MIP_{WUI_ext}	\$17,648	-\$18,779	\$78,052	5.6%	400
$MIP_{Hriskscore}$	-\$383	-\$1,060	\$346	-0.1%	400

[a] All values are measured in 2013 dollars.

[b] In addition, drop in property value decrease with the increase in radius, from \$39,126 for 10km radius, to \$24,619 for 15km radius, \$10,645 for 20km radius and \$6,215 for 25km radius. Accordingly, drop in assessed value varies from 2% to 12%.

Table 7.6: Meta-analysis of MIP estimates using the random-effects model[a]

MIP estimate	Pooled estimate	95%CI (LL)	95%CI (UL)	% change in assessed value (based on mean estimates)	p-Value for H_0: no effect
Wildfire event					
MIP_{Dist}	$3,461	$3,188	$3,734	1.1%	0.00
$MIP_{Firenum}$[b]	$14,375	$13,821	$14,928	4.6%	0.00
Wildfire risk					
MIP_{Comp_high}	$7,040	$6,636	$7,444	2.2%	0.00
MIP_{Comp_ext}	$10,662	$9,831	$11,493	3.4%	0.00
MIP_{WUI_high}	$19,316	$17,911	$20,721	6.1%	0.00
MIP_{WUI_vhigh}	-$24,284	-$26,469	-$22,099	-7.7%	0.00
MIP_{WUI_ext}	$22,611	$20,240	$24,981	7.2%	0.00
$MIP_{Hriskscore}$	-$565	-$599	-$531	-0.2%	0.00

[a] All values are measured in 2013 dollars.

[b] In addition, drop in property value decrease with the increase in radius, from $25,134 for 10km radius, to $22,277 for 15km radius, $11,910 for 20km radius and $5,392 for 25km radius. Accordingly, drop in assessed value varies from 1.6% to 8%.

Table 7.7: Kolmogorov-Smirnov (KS) test results for the standard error of MIP estimates

Model Characteristics	**Standard error of MIP_{Dist}**			**Standard error of $MIP_{Firenum}$**		
	Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
Data for housing prices						
Assessed value	792	121	2,611	14,253	365	1,032,194
Estimated sale price	1,114	149	8,356	6,122	715	117,916
KS test	Reject the null hypothesis of identical distribution					
Functional form						
Semi-log	1125	160	8,356	10,496	381	956,760
Double-log	781	121	4,625	9,879	365	1,032,194
KS test	Reject the null hypothesis of identical distribution			Fail to reject the null hypothesis		
Spatial dependency structure						
OLS	752	121	5,138	5,291	365	34,441
Spatial	975	128	8,356	10,732	383	1,032,194
KS test	Reject the null hypothesis of identical distribution					

Table 7.8: Mega-analysis of MIP estimates as a function of data and econometric modelling techniques

Model characteristics		**Meta-regression Model 1**	**Meta-regression Model 2**
		Dependent variable=MIP_{Dist}	**Dependent variable=$MIP_{Firenum}$**
Data			
Property value	Assessed value	7867***	25313.4***
		(321.3)	(4276.8)
Past wildfire events/occurrence	7-yr time window	-475.9	14531.8***
		(317.9)	(4531.5)
Buffer zone radius	15km		-79622.9***
			(4509.5)
	20km		-61512.7***
			(5808)
	25km		-50024.7***
			(6480)
Wildfire risk data	Composite risk (County)	2611.8***	-96407.9***
		(724.2)	(7075.2)
	Composite risk (WUI area)	6896.6***	-96663.4***
		(592.8)	(6148.4)
	WUI risk	6650.9***	-106439.7***
		(589.1)	(6058.1)
	House risk	6463.7***	-122424.8***
		(499)	(4971)
Econometric Specification			
Functional form	Semi-log	1203.5***	-28243.9***
		(305.8)	(3280.9)
Spatial dependency and weight matrix	Lag, WM=Knn4	-1061.2	16606.5*
		(716.6)	(8835.9)
	Lag, WM=Knn8	-1456.2**	-13677.6
		(699.5)	(9288.4)
	Lag, WM= Distance inverse	-80.19	-1812.4
		(757.5)	(10063.4)

Table 7.8: Mega-analysis of MIP estimates as a function of data and econometric modelling techniques (cont'd)

Model characteristics	Meta-regression Model 1 Dependent variable=MIP_{Dist}	Meta-regression Model 2 Dependent variable=$MIP_{Firenum}$
Error, WM=Knn4	-211.5	-1590.7
	(744.9)	(9929.9)
Error, WM=Knn8	-382.4	-6105.4
	(733.3)	(9786)
Error, WM= Distance inverse	-203.8	-4366.2
	(697.2)	(8408.1)
General, WM=Knn4	-1935.4***	-80171.9***
	(715)	(8643.9)
General, WM=Knn8	-3332.2***	-25032.6***
	(689.5)	(8914.7)
General, WM= Distance inverse	-390.7	35112.5***
	(690.3)	(8360.3)
Constant	-4589.7***	166815.4***
	(730.2)	(9201.1)
N	400	1,600
Adj. R^2	0.68	0.7

*** significant at 1%, ** significant at 5%, * significant at 10%. Standard Errors are in parentheses.

Figure 7.1: Kernel density estimates of MIP_{Dist} across models that use assessed value data and models that use estimated sales price data

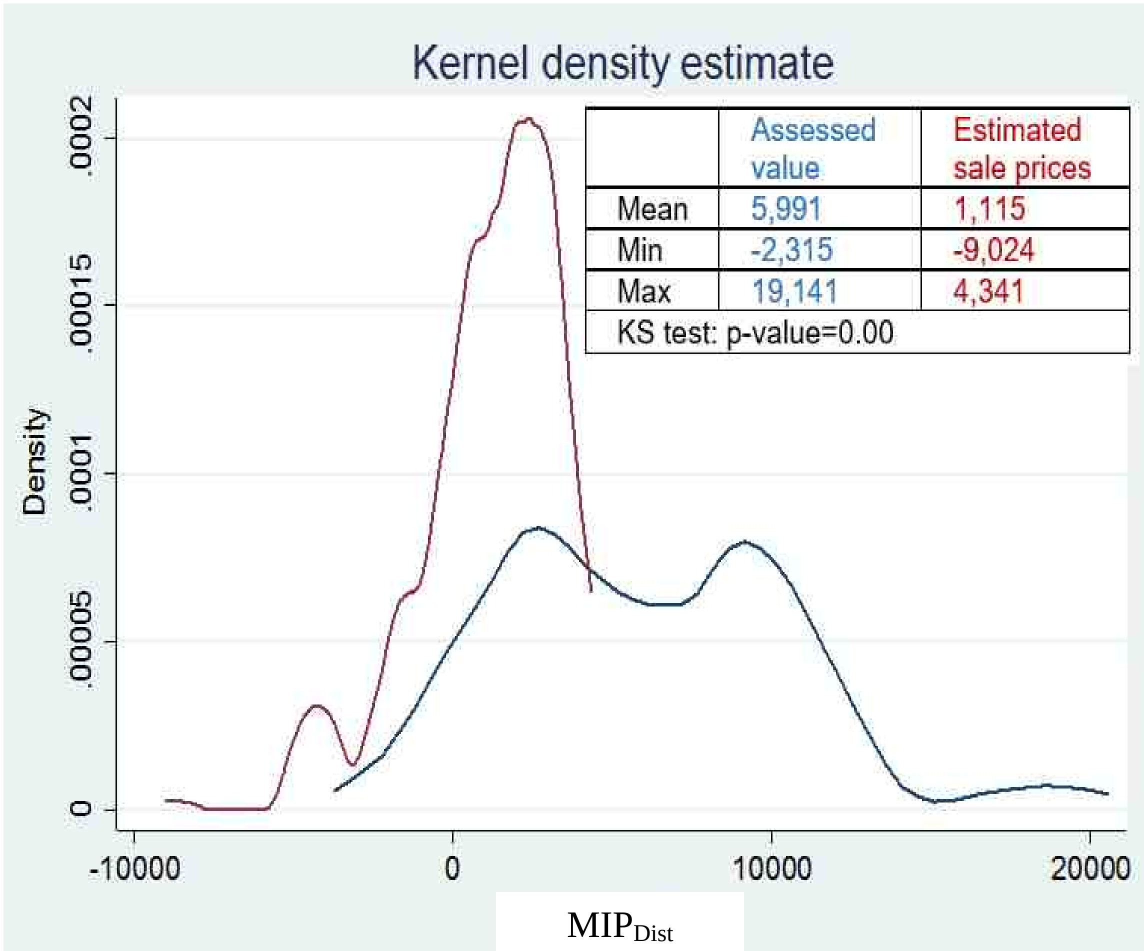


Figure 7.2: Kernel density estimates of MIP_{Dist} across models that use fires burned in the last 7 years (7-year time window) and fires burned in the last 15 years (15-year time window)

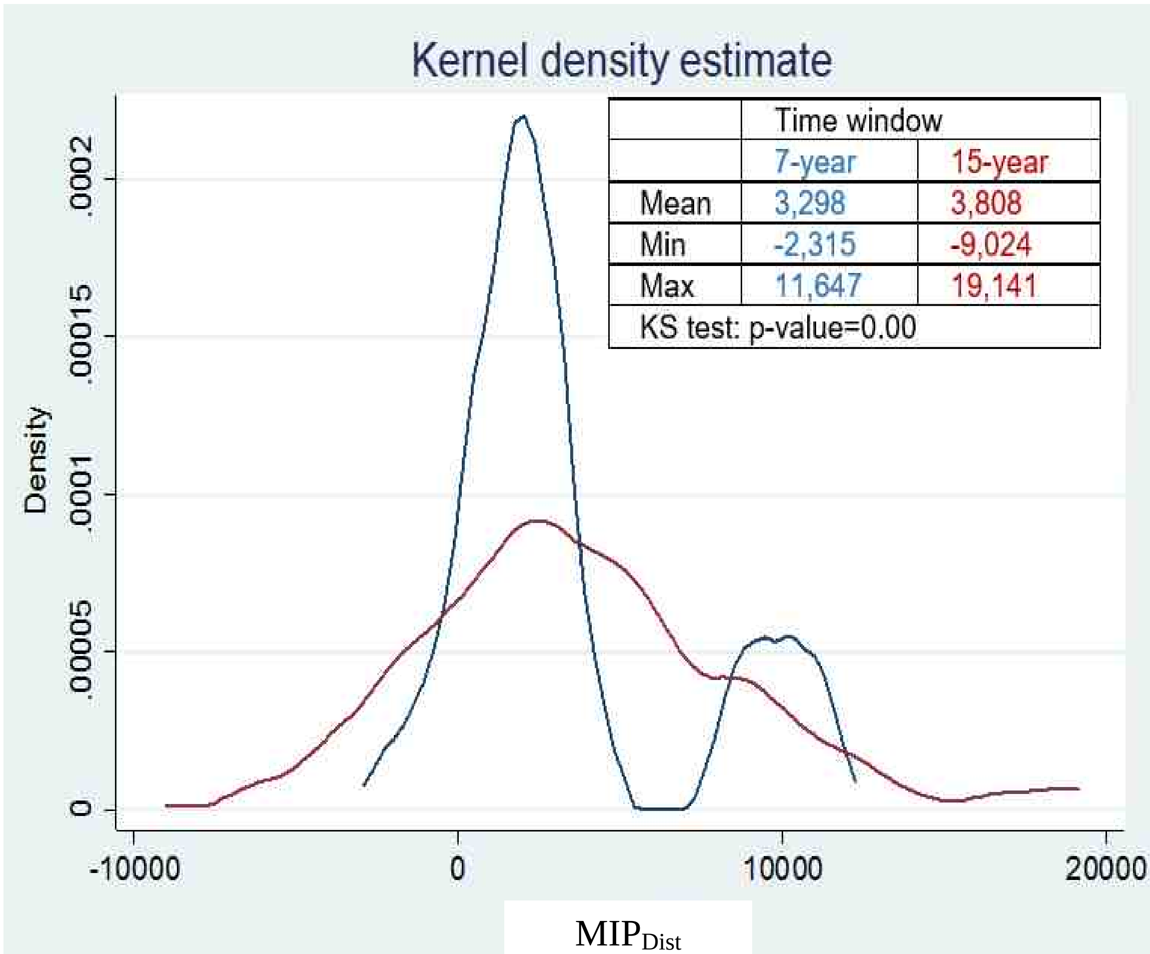


Figure 7.3: Kernel density estimates of MIP_{Dist} across models that use composite risk covering Non-WUI area and WUI area

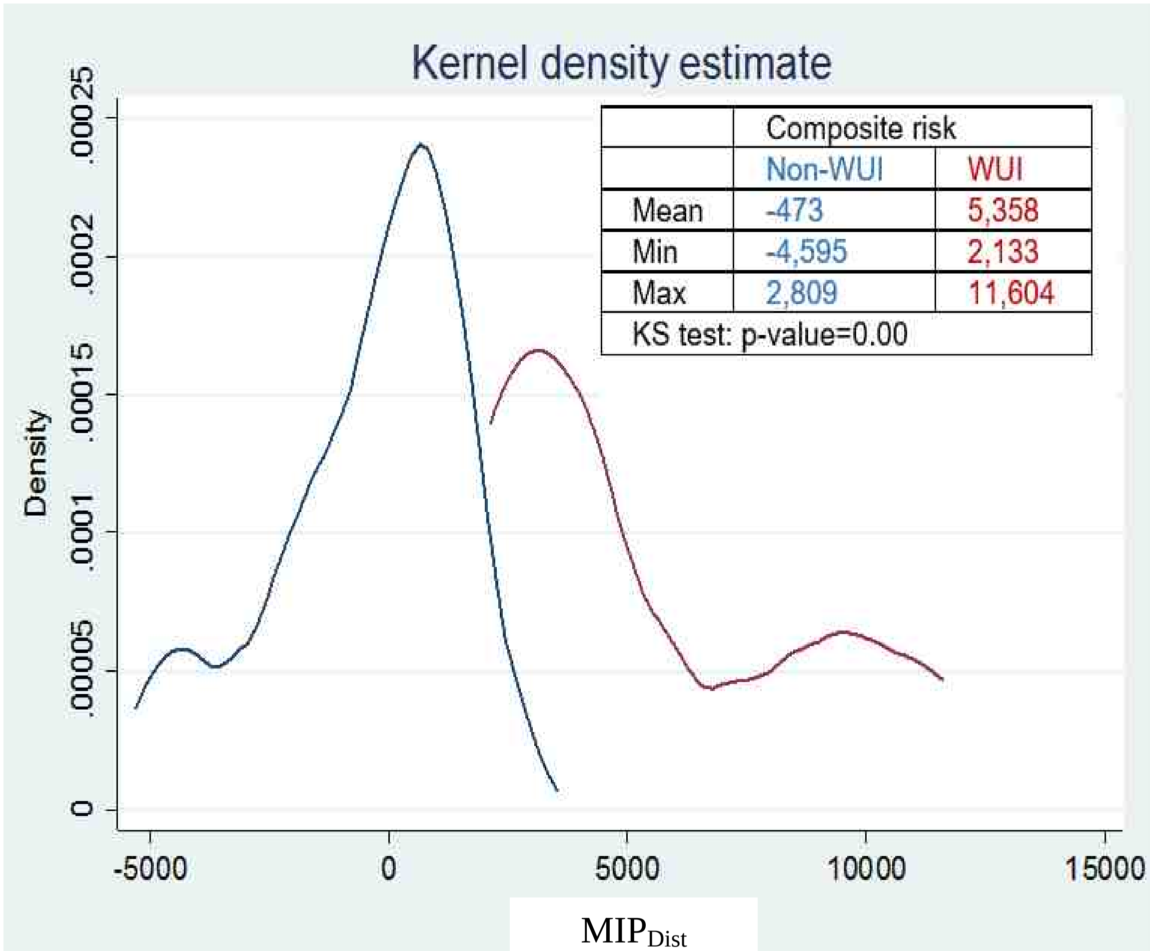


Figure 7.4: Kernel density estimates of MIP_{Dist} across models that use semi-log functional form and models that use double-log functional form

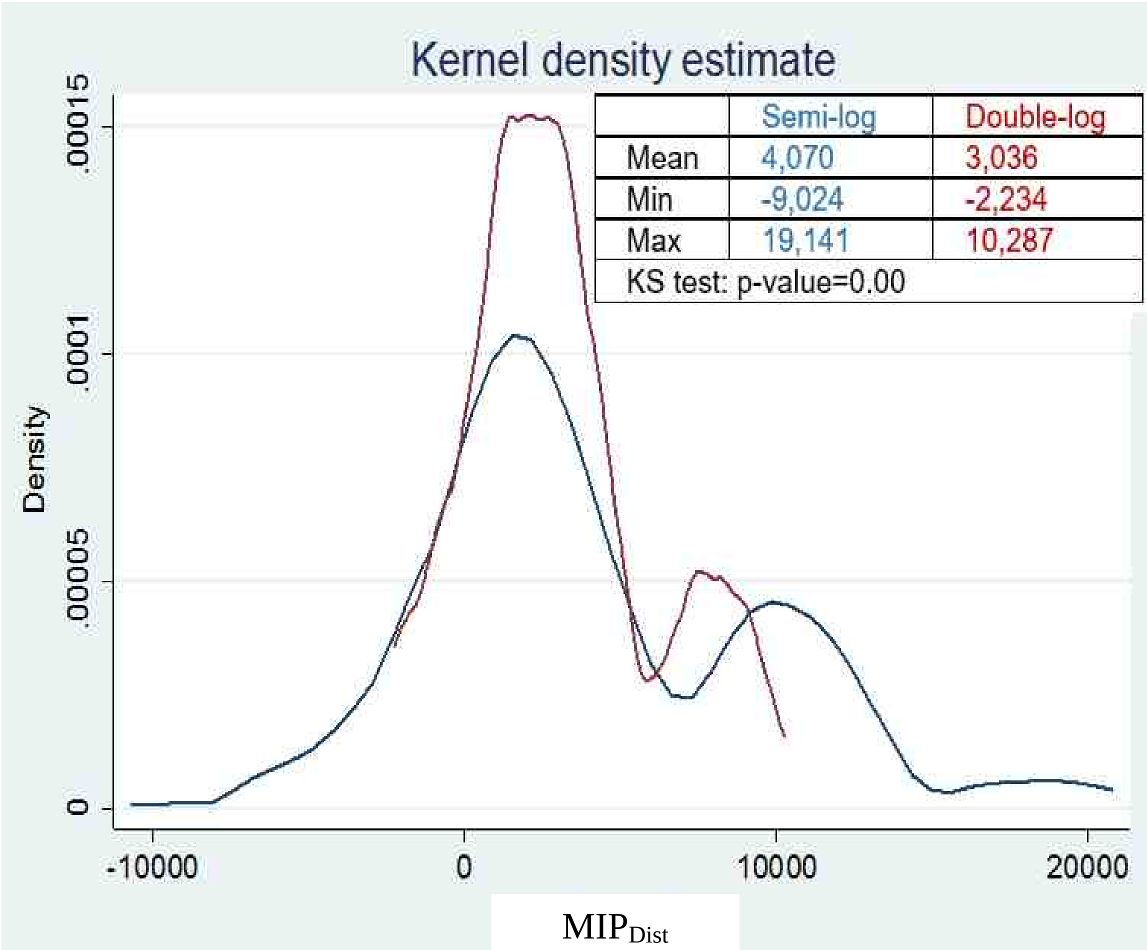


Figure 7.5: Kernel density estimates of MIP_{Dist} across OLS models and spatial autoregressive models

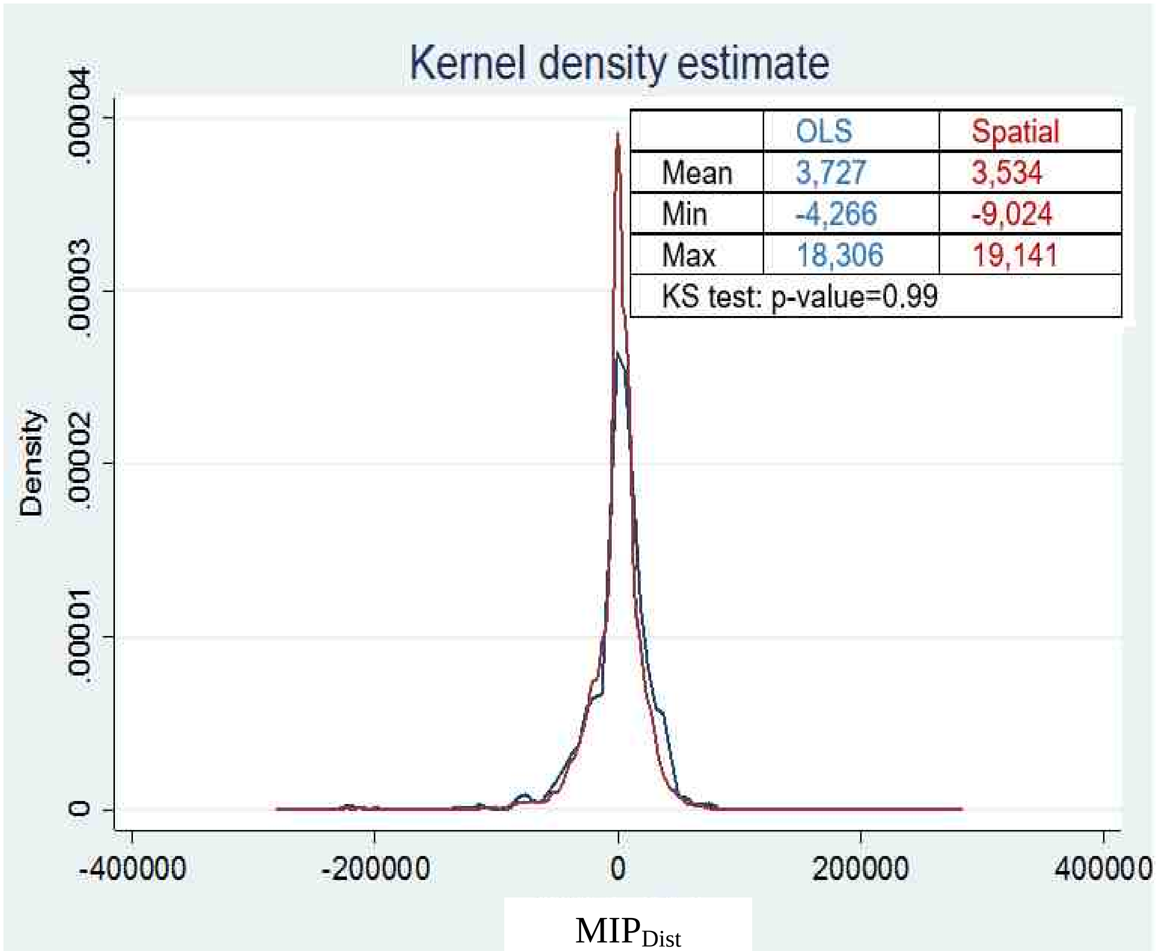


Figure 7.6: Kernel density estimates of $MIP_{Firenum}$ across models that use assessed value data and models that use estimated sales price data

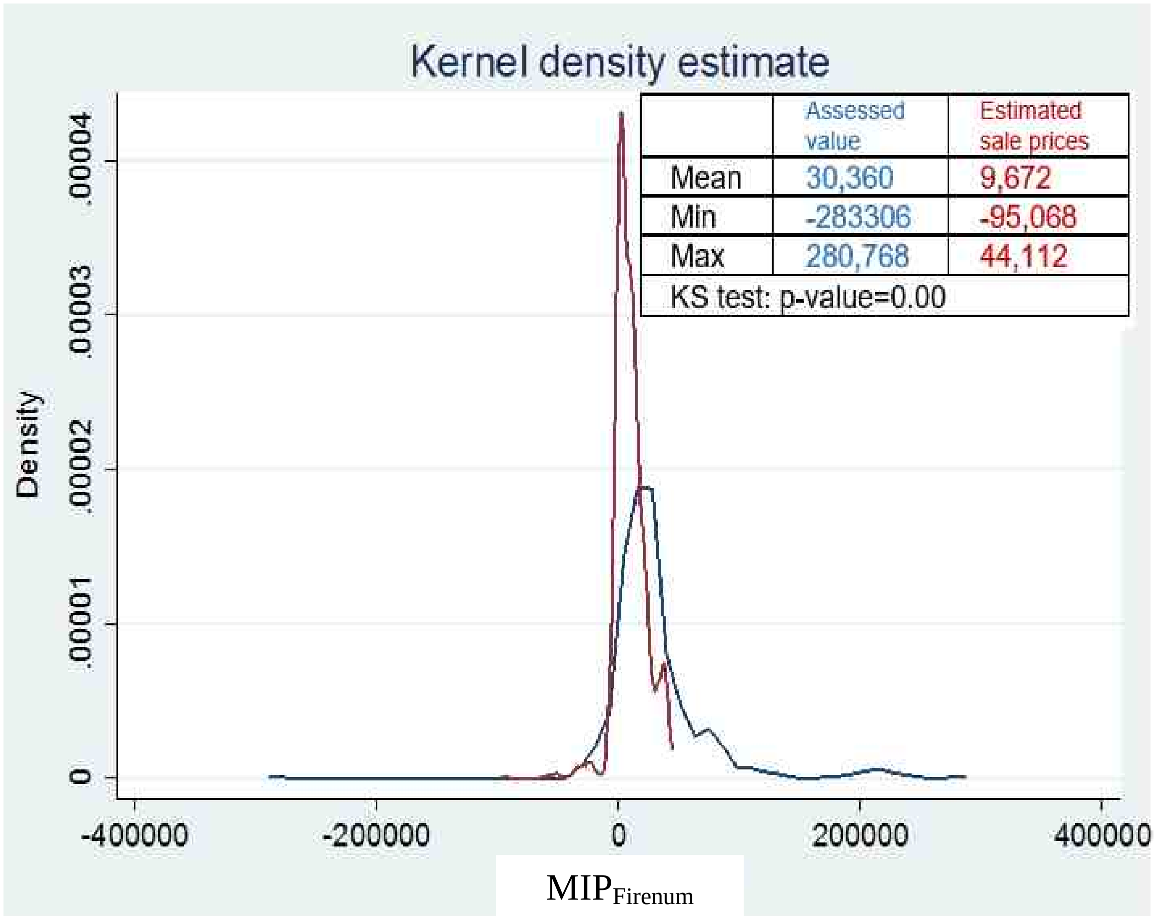


Figure 7.7: Kernel density estimates of $MIP_{Firenum}$ across models that use 10, 15, 20 and 25km radius

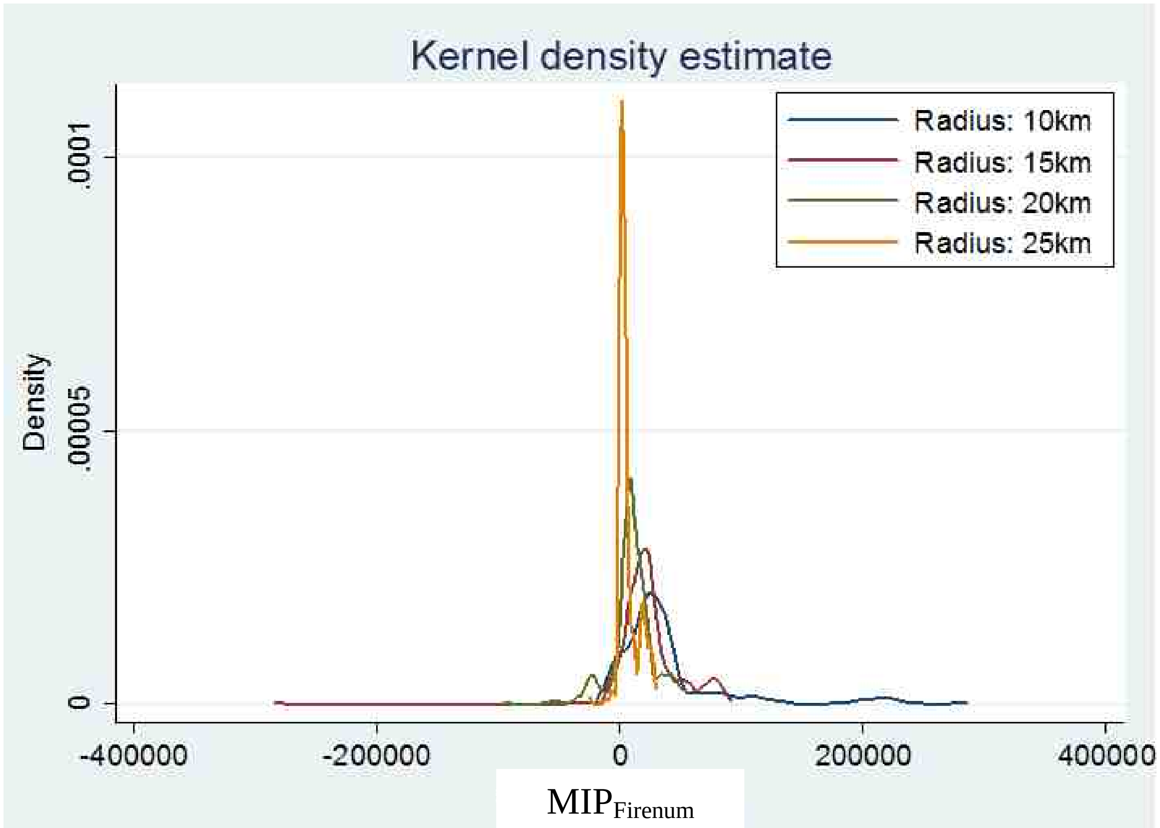


Figure 7.8: Kernel density estimates of $MIP_{Firenum}$ across models that use composite risk covering Non-WUI area and WUI area

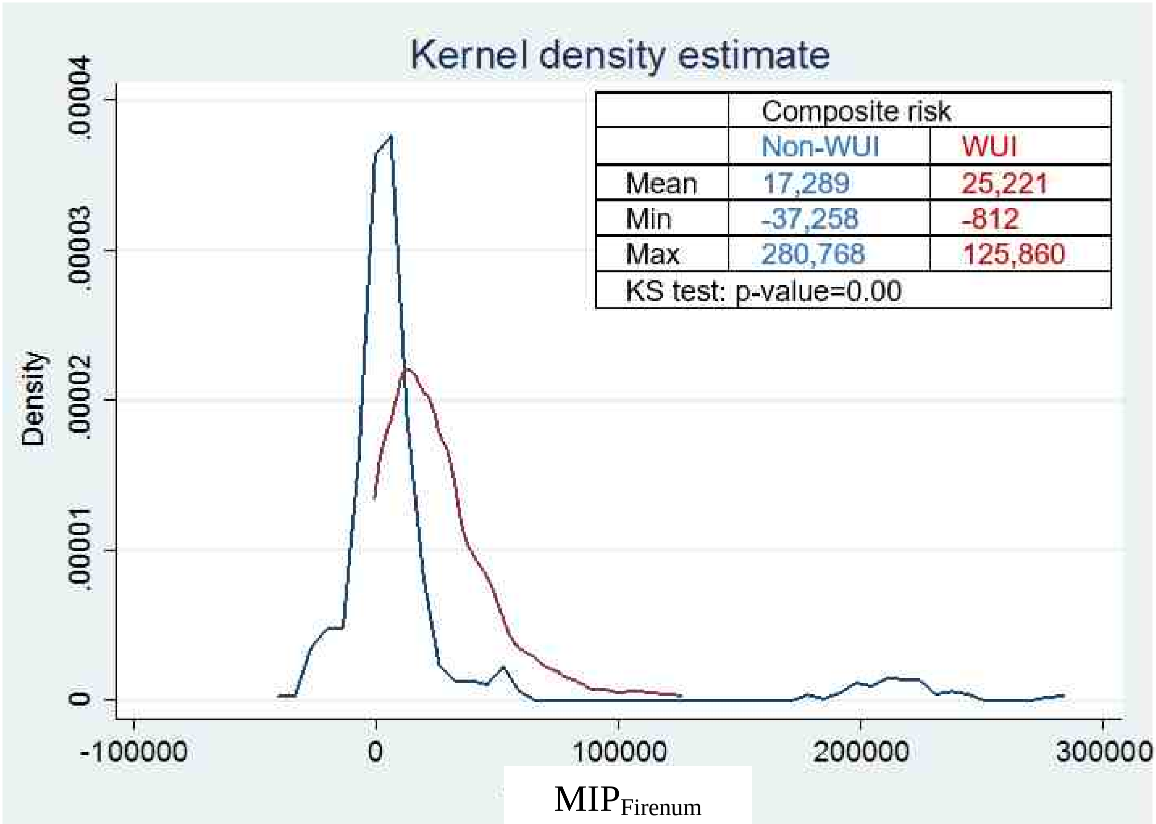
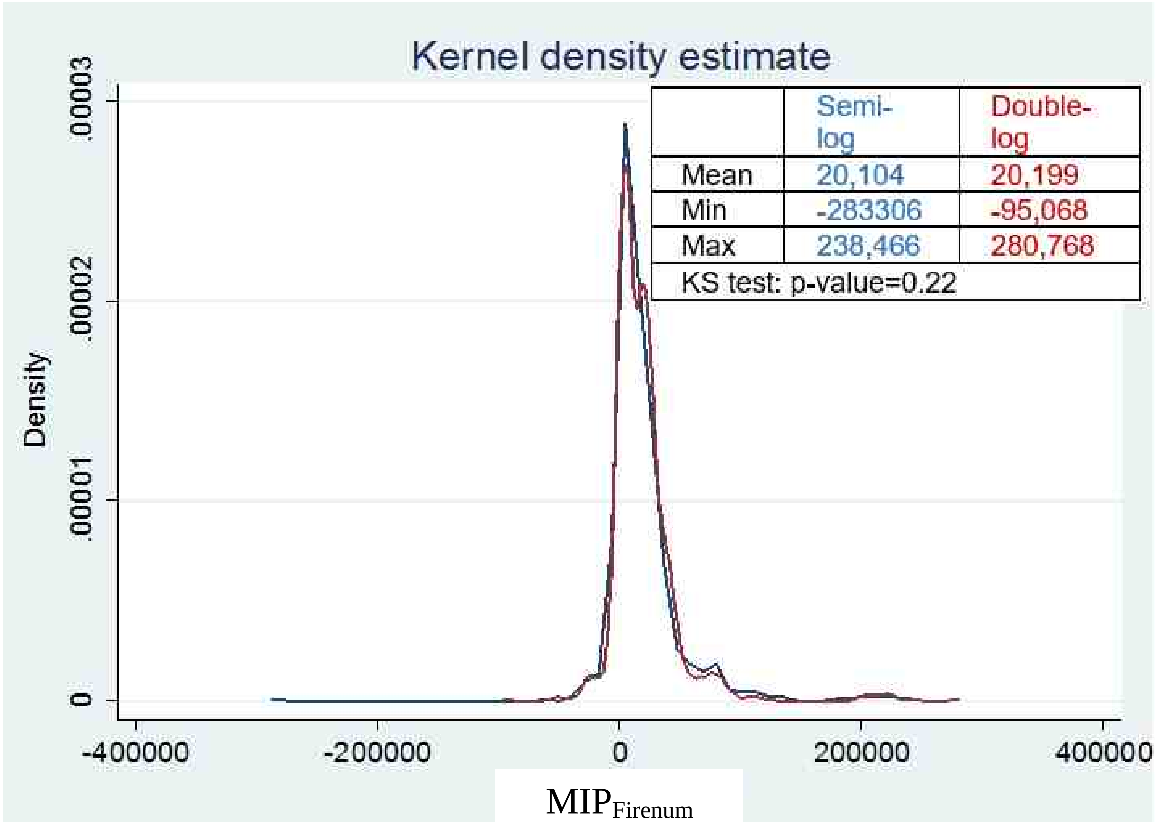
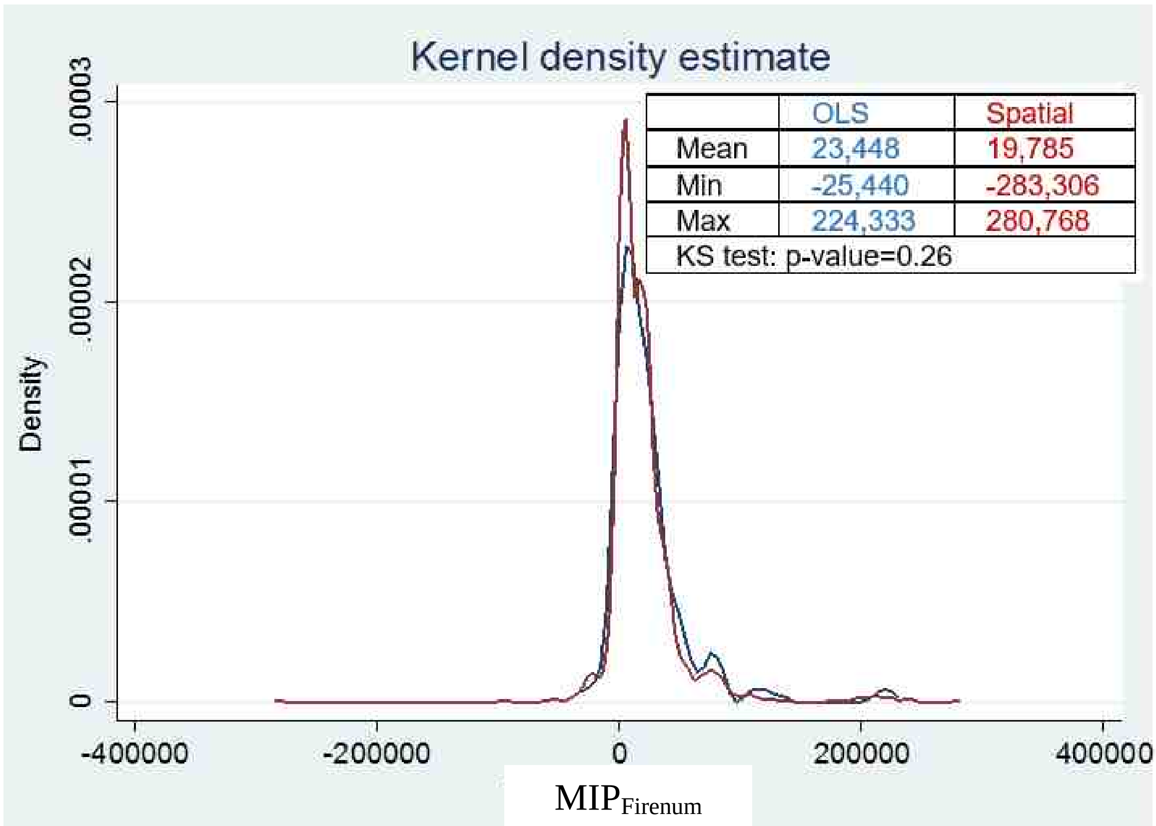


Figure 7.9: Kernel density estimates of $MIP_{Firenum}$ across models that use semi-log functional form and models that use double-log functional form



	Semi-log	Double-log
Mean	20,104	20,199
Min	-283306	-95,068
Max	238,466	280,768
KS test: p-value=0.22		

Figure 7.10: Kernel density estimates of $MIP_{Firenum}$ across OLS models and spatial autoregressive models



Chapter 8 Conclusion and policy implications

8.1 Conclusion

This analysis utilizes spatial autoregressive hedonic models to investigate the joint effect of past wildfire event/occurrence and current risk on property values. I contribute to the literature by systematically investigate wildfire effects using a variety of data and econometric modeling techniques. First, the unique data sets allow us to estimate hedonic models using two data sources for property value; two measures for past wildfire event/occurrence (combined with varying time window and buffer zones) and three risk measures. Secondly, I use two hedonic functional forms and a variety of spatial dependency structures in the hedonic model to examine wildfire effects. The variations in the data and modeling techniques, in turn, enable comparison of wildfire effects across alternative models. I then employ an internal meta-analysis approach to examine how the effects of wildfire vary with data and econometric modeling decisions. This analysis is the first application of meta-analysis on hedonic studies concerned with wildfire effects on housing market.

Results of hedonic models show the negative effect of past wildfire event/occurrence, which is consistent with Stetler et al. (2010) and Huggett Jr et al. (2008). However, the influences of wildfire risk are mixed, depending on the measurement of risk, level of risk and geographic area. Since risk assessments vary with regard to input data, this result is not surprising. There are still two points worth noting. First, the effects of the risk change when risk reaches a certain threshold. At lower levels of risk, property values increase with the increase in wildfire risk. Once risk level rises above a certain threshold, the relationship tends to be negative or insignificant. Secondly, the effects of composite risk differ across geographic area. In the Non-WUI the positive effects of amenities dominate, and therefore fire risk has a positive effect on property values. In the WUI, the negative effects of wildfire risk offset, or even exceed the positive effects of amenities, resulting in a non-significant or negative relationship. As stated earlier, Donovan et al. (2007) also examined the effects of wildfire risk on property values and found that wildfire effects change after publication of risk on the website. However, it is not clear whether risk assessment used in their study is directly comparable to one of risk assessments in this analysis since the algorithm used to calculate risk rating is not published.

Meta-analysis results show that models that use assessed value data not only give higher R^2 but also find more significant estimates and larger MIP estimates than models that use estimated sales prices data. However, the assessed value models do not necessarily yield estimates with smaller standard errors. Second, ignoring spatial autocorrelation either leads to overestimate of MIP or it has no significant effect on MIP estimates. Third, the measurement of wildfire risk significantly influences the effects of fire event/occurrence. This result reveals the importance of joint estimation of wildfire events and risks, and ignoring wildfire risks in hedonic models may yield inaccurate estimates.

8.2 Limitations and future research

First, our study is limited in that I utilize the estimated sales price, which is derived from the mortgage amount. Previous hedonic literature has exploited either assessed value or the actual sales price as the dependent variable. There has been no empirical analysis using the estimated sales price in hedonic model, and therefore it is not clear how this would affect the estimates of wildfire effects. Future research might further explore this issue focusing on an area with both assessed value and the actual sales price data available.

Secondly, for past wildfire event/occurrence data, this research only used fires burned larger than 10 acres. Further research can examine a more complete activities of fires by including fires burned less than 10 acres. One can then compare the results from these two models and comprehensively understand the effects of wildfire size on property values. Further, for both measures of past wildfire event/occurrence, this analysis focus on multiple fires. One can select one big fire and exploit differences-in-differences approach to investigate the effect of a single fire.

Finally, estimation of past wildfire event/occurrence effects is complicated by the fact that fires are generally burned in wildland area, which also have high amenity values. Similarly, the roles of wildfire risk in housing market are double edged: factors contributing to high wildfire risk also tend to have high amenity values, such as wood roof. One extension is to decompose risk ratings to the underlying factors used to compute the rating. For example, two parts are used to compute WUI risk rating: fire environment (e.g., fuel, slope) and defensibility (e.g., length of dead-end road, water availability). One can then regress property value on defensibility, or even length of dead-end road rather than the overall risk rating. This may help to distinguish the effects of amenities from the effects of risk. For example, length of dead-end road captures wildfire risk but not amenity. Another extension is to use stated preference method (e.g., contingent valuation or choice experiment) to further explore tradeoffs between wildfire risk and amenity. Wildfire effects differ across the Non-WUI and the WUI area. Thus, the sample should include homeowners in both areas. First, it could identify attributes or risk factors that are important to homeowners. Second, it could measure tradeoffs between a variety of risk factors, quantify homeowners' willingness to pay for a certain risk factor or a bundle of risk factors. Third, it could capture the difference in homeowners' preference on varying risk factors across the Non-WUI and the WUI area.

8.3 Policy implications

To efficiently allocate resources among competing projects, policy makers need to evaluate the full cost of wildfires. The costs of suppression cost and rehabilitation are relatively easy to measure. However, the costs of wildfires go beyond these direct costs. My results indicate that houses that are not physically damaged by fires will suffer a price drop, suggesting that these costs should also be measured and factored into policy decisions. Given the rapid development in the WUI, together with the growing threat from wildfires, the impact of wildfires on housing market is expected to increase. Our findings help capture these escalating hidden costs. Fire managers can use these results to estimate the impact of fire on the housing market.

Furthermore, our meta-analysis results indicate that the analysts' choice of data and econometric modeling decisions significantly affect the estimated wildfire effects. This finding is consistent with other meta-analysis results. Researchers have to be cautious in interpreting empirical evidence regarding wildfire effects on property values; policy implications have to be drawn with caution as well.

Our findings of the negative economic impact of wildfire on property values also shed light on strategies for communication and outreach. National fire policies place a great deal of emphasis on pre-fire mitigation and preparedness by private landowners, homeowners and communities in fire-prone areas (e.g., the National Fire Plan, Firewise Community/USA Recognition Program, Healthy Forest Restoration Act). A comprehensive body of research demonstrates that multiple factors have an impact on mitigation decisions, such as knowledge about wildfire, past experiences with wildfire, perceived wildfire risk and effectiveness of risk reduction activities (Brenkert–Smith, Champ, & Flores, 2006; Martin, Bender, & Raish, 2007; Paton, 2008; McCaffrey, Stidham, Toman, & Shindler, 2011; Ascher, Wilson, & Toman, 2013; Champ, Donovan, & Barth, 2013; Fischer, Kline, Ager, Charnley, & Olsen, 2014; Meldrum et al., 2014). Most WUI residents recognize wildfire risk to be high, however awareness alone is not sufficient for effective mitigation activities. One key factor affecting mitigation decisions is the cost of mitigation efforts and their potential benefits (Steelman, 2008). Homeowners are more likely to undertake action when the benefits outweigh the costs. Conveying the potential price drop caused by the threat of wildfire might encourage homeowners to take into account the non-market cost of wildfire. Knowledge of the negative impact on the value of their property tends to increase the expected benefits of mitigation actions, and thus the likelihood of mitigation.

Further, our findings about spatial autocorrelation would encourages homeowners to work together to take fire-mitigation activities. The existence of spatial autocorrelation implies that the change in one house’s price/characteristics has a significant effect on neighboring sites. Thus one homeowner’s risk reduction activities would not only increase the value of his home but also the value of neighboring houses, implying the benefit of reduction activities is shared among neighboring properties. Furthermore, research show that neighbors play a crucial role in mitigation decisions (Shafran, 2008;

Brenkert-Smith, 2010; Dickinson, Brenkert-Smith, Champ, & Flores, 2015). Residents are more willing to take mitigation action on their own property if their neighbors also take risk mitigation measures. The dissemination of the positive externality of mitigation activities help build relationships between neighbors, encourage them to take mitigation actions on individual properties as well as throughout communities, and help facilitate Firewise and Fire Adapted Communities.

With the growing wildfire problem, assessing wildfire risk also grows in importance. Our results indicate that wildfire risk has a significant effect on property values and further, this effect varies depending on the scale of the risk assessment. The findings provide support for conducting risk assessment at various geographic scales. Risk assessments developed at different spatial scales vary regarding input data. Generally, assessments covering large geographical areas, such as at the state or county level, tend to concentrate on three factors: fuel, topography and weather; community-specific or site-specific assessment also takes into account characteristics of a community, vegetation near the house or characteristics inside the property boundary (e.g., building design and material). Broad-scale assessment facilitates the direct comparison of fire risk between geographic areas. However, it generally ignores community-specific or site-specific characteristics, and cannot be used to provide more accurate risk reduction recommendations. To develop risk mitigation plans both at the macro level and at the community and home level, policy makers must have access to multi-level risk assessment. Moreover, risk assessments conducted at varying geographical scales can provide researchers and policy makers with a greater understanding of the effect of risk on the housing market.

Appendix A

Figure A.1: Wildland Fire Association Hazard Assessment Form

Community fire risk assessment form

HAZARD ASSESSMENT FORM
WILDLAND FIRE ASSOCIATES

COMMUNITY/AREA______________________________________
DATE______________

1. FIRE ENVIRONMENT

A. FUEL HAZARD (NFPA 299) – (Averaged)	**POINTS**
No Fuels = 0	
Light fuels (Grass, Low Shrubs) NFFL1,2,5,8 = 1	
Medium Fuels (Brush, Large Shrubs, Small Trees) – NFFL 9 = 3	
Heavy Fuels (Timber, slash, Large Brush, Bosque) NFFL 4,10 = 5	
B. SLOPE HAZARD (NFPA 299, FEMA) – (Averaged)	
Flat to Mild Slope (09.9%)= 1	
Mild to Medium Slope (1019.9%)= 2	
Medium to Moderate Slope (2039.9%)= 3	
Moderate to Extreme Slope (40% +) = 5 ASPECT (N & E = 1; S & W = 2)	
C. SPECIAL HAZARDS (Averaged)	
Insect kill (Piñon, ponderosa pine), mistletoe = 0–2	
Chimney, Steep Canyon, Saddles = 3–6	
Other (describe)	

Total

2. DEFENSIBILITY

A. ACCESS Length of DeadEnd Road (consider bridges, turnouts, bordering fuels, turnaround space, etc.)	**POINTS**
Less than 600 feet 0 Points	
600 to 1,000 feet 1 Point	
1,000 to 1,320 feet 3 Points	
Greater than 1,320 feet 5 Points	
B. STRUCTURE TYPE – (Averaged)	
Flameresistant roofing/siding = 0	
Flammable roofing/siding = 1–3	
C. CLEARANCE/DEFENSIBLE SPACE (Averaged)	
Fuel Break > 30 ft. (trees pruned 6 ft., firewood >10 ft. away) = 0–3	
Fuel Break < 30 ft. (defensibility marginal) = 4–6	
D. WATER AVAILABILITY (Averaged)	
Well Water only – limited water source = 2	
Community Water – uninterruptible water source = 0–1	

Total

Figure A.2: Individual-level house risk assessment

Santa Fe County Fire Dept.
Wildland Division

http://www.sfcfire-wildland.com/

Wildfire Hazard Assessment

address

community

SITE HAZARD RATING:		RATING
ACCESS and VISIBILITY: Can emergency personnel find and access?		
Driveway < 150 feet long Driveway > 150 feet with adequate turnaround Driveway > 150 feet with inadequate turnaround	0 3 5	
Driveway width more than 12 feet Driveway width less than 12 feet	0 5	
No overhead branches below 14 feet Obstructing overhead branches below 14 feet	0 5	
No bridges or bridges with no restrictions Inadequate surface / bridges for emergency vehicle	0 5	
Road grade level or less than 10% Road grade over 11%	0 5	
No gate / non=-locking gate Locked gate restricting access	0 5	
Address visible from road (on house/end of drive) Address not visible from road or not found	0 5	
SURROUNDING TREES: Choose predominate type within 30ft of home		
No trees within 30 feet Hardwoods (trees with deciduous leaves) Mixed (hardwoods and conifers/evergreens) Conifers / Evergreens (non-deciduous)	0 4 7 10	
LADDER FUELS: Can fire spread from surface to aerial fuels?		
Include low limbs, underbrush, vines, etc. — No Yes	0 5	
FUEL CONNECTION: Are ground fuels touching or within 3ft of home?		
Include ornamental shrubs, leaves, grass, weeds, mulch beds, etc. — No Yes	0 5	

		RATING
GROUND COVER: Choose primary type of ground cover within 30ft of home		
Sand, gravel, etc. (non-combustible) Grasses, up to 6" tall Grasses over 6" tall (heavy weeds, etc) Herbaceous understory or forest leaf litter Shrubs with leaves Shrubs with needles (spreading juniper, etc)	0 3 10 15 5 7	
SLOPE OF PROPERTY: What is average slope around structure?		
Gradual (0-10%) Moderate (11-30%) Steep (over 30%)	0 5 10	
FIREWOOD, DEBRIS or COMBUSTIBLES: Where are the jackpots located?		
Include firewood piles, brush piles, stored lumber, outdoor furniture, etc. None More than 30ft from home 3ft -30ft from home 0ft - 3ft from home	0 1 5 10	
FLAMMABLE MATERIALS: Where are highly flammable materials stored?		
Include gas cans, gas grills, lawnmowers, pesticides, etc. None/Unknown More than 30ft from home 3ft -30ft from home 0ft - 3ft from home	0 1 5 10	
OTHER POTENTIAL HAZARDS: Are there any external hazards present ?		
Include outbuildings, propane tanks, etc within 30 feet of structure — No Yes	0 5	
TOTAL SITE HAZARD RATING:		

Wildfire Hazard Assessment

STRUCTURE HAZARD RATING:			RATING
ROOFING MATERIALS: What is the roof covering of the home?			
Metal, Slate, Tile or Class A Shingles		0	
Rolled roofing or non-rated roof material		5	
Wood (cedar shingles or shakes)		15	
FOUNDATION: What type of foundation does the home have?			
Enclosed (fireproof ie: concrete, metal, adobe)		0	
Enclosed with wood or vinyl sheeting		5	
Open air foundation (piers, stilts, etc.)		10	
EXTERIOR WALLS: What is predominate outer wall covering?			
Brick, Stone or Metal		0	
Vinyl or Wood		5	
VENTS and EAVES: Are these protected from flying embers?			
Enclosed with plastic or metal screens		0	
Exposed wood, open soffits or unscreened vents 5			
ATTACHMENTS: Are there any attachments to the structure?			
Includes decks, overhangs,	No	0	
fenced, trellises, etc.	Yes	5	
FUEL TRAPS: Any areas where leaves/debris can accumulate?			
Include window wells, under steps,	No	0	
foundation indents, etc.	Yes	5	
TOTAL STRUCTURE HAZARD RATING:			

recommendations

HAZARD REDUCTION FACTORS: (Choose any)		RATING
SITE:		
Ladder fuels removed within 30ft of house	-1	
Grass mowed/watered within 30ft of house	-1	
Leaves/needles raked within 30ft of house	-2	
3 feet of gravel or non-flammable material around house	-3	
STRUCTURE		
Regularly cleaned roof and gutters	-1	
Deck skirting non-flammable / screened	-3	
OTHER		
Firefighting equipment available (hose, ladders, etc)	-1	
Useable water supply nearby(pool, pond, hydrant, etc)	-3	
TOTAL HAZARD REDUCTION RATING:		

CWPP HAZARD RATING FOR AREA

Low=0
Moderate=10
High = 20
Very High=30
Extreme= 35

CWPP	+	SITE	+	STRUCTURE	-	REDUCTIONS	=	grand total

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