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Forest density preferences of homebuyers in the wildland-urban interface

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ABSTRACT

In the fire-prone Western U.S., the scale of surrounding forest density can be realized by homebuyers as an amenity for aesthetics and cooling effects, or as a disamenity in terms of wildfire risk. There has been a lack of academic attention to understanding this duality of forest density preferences for homebuyers in at-risk Wildland Urban Interfaces (WUIs). To fill this gap, we investigated the influence of forest density on WUI house sales in four high fire-risk zones in dry, mixed conifer forests of the Western U.S with a spatial hedonic pricing model. Explanatory attributes related to house structure, neighborhood, and environmental amenities were assessed, along with a set of WUI variables that included forest density ranges at two buffer levels— a 100 m radius level and a 500 m radius level. Results indicate a strong preference for lower forest density at the 100 m level, but a countering preference for higher forest density at the larger 500 m buffer. These findings suggest the need to reconsider broad approaches in public awareness campaigns and regional planning, as well as fire management policies and strategies. Preference for higher density forests implies that if left to homeowners, fuel treatments in public spaces will be underinvested.

1. Introduction

Expansion of the wildland-urban interface (WUI) has been identified as the primary cause of rapid increases in wildfire-related losses in the United States (Keeley et al., 1999; Radeloff et al., 2005), Canada (McFarlane et al., 2011; Goemans and Ballamingie, 2013), Australia (Mell et al., 2010) and the Mediterranean (Darques, 2015). This is particularly true for ecosystems that once burned frequently with low-moderate intensity before old-growth logging, overgrazing, and, perhaps most significantly, fire exclusion (Covington, 2000). Many forests, especially across the western United States, have experienced declining ecological health and increased risk of uncharacteristically large and severe wildfires (GAO, 2009a; GAO, 2015). Reducing wildland fire risk and damage within residential developments in the WUI has become one of the most pressing issues in managing U.S. public lands (Stetler et al., 2010).

Some of the most complicating factors for managing wildland fire risk are the costs of fire suppression and risk reduction, and who pays for fire management. The costs of fighting wildland fires have been escalating continuously in the United States, doubling to more than $2.9 billion annually during 2001–2007 from an average $1.2 billion annually during 1996–2000 (GAO, 2009b). Many studies have investigated the factors affecting wildland fire suppression costs (e.g. Calkin and Gebert, 2006; Gebert et al., 2007; Liang et al., 2008; Abt et al., 2009; Yoder and Gebert, 2012). The primary factors that explained the majority of variation in wildland fire suppression costs, other than fire size, were those related to the WUI, including proximity to the WUI and the proportion of private land within fire perimeters. About 897,000 properties (estimated reconstruction value at $237 billion) in the western U.S. are now located in high or very high wildfire risk areas (CoreLogic, 2015). Expansion of the WUI is likely to continue in the future, especially in the intermountain west states where the risk of large and severe fires is ever increasing (Theobald and Romme, 2007). The majority of wildfire suppression costs are born at the federal level (Gude et al., 2008). Although more than 30% of total wildfire costs can be attributed to defending private residences (Rasker, 2015), there is little incentive for state, county, or local governments who make land use decisions to curb the development within the WUI (Gude et al., 2008; Abrams et al., 2015).

Homebuyers, along with locally elected officials, may underestimate the dangers and financial consequences of fire-prone forests (Abrams et al., 2015). By assuming much of the fire suppression and management burden, the federal government may be providing a perverse incentive to locate in hazardous areas (Busby and Albers, 2010). Homebuyers' decisions to buy homes in the WUI are influenced by their preferences for

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natural amenities as well as their perceived risk of natural disasters. Forest cover provides certain amenities, including shade, privacy, noise reduction and aesthetics, while too many trees may manifest as disamenities for blocking viewsheds and increasing the chance of home ignitions during wildfires. This duality makes it hard to effectively communicate with home owners about the needs for reducing forest density in the WUI and to inform policy decisions that need to be applied in the landscape level. With forest cover representing both amenities and disamenities in high fire risk areas, there is a need to understand the influence of surrounding forest density on property values in the WUI (Venn and Calkin, 2011; Hansen et al., 2014).

In this study, we focus our attention on properties in the dry mixed-conifer WUI ecosystems of the American west where the rising trend of wildfire risk is particularly severe. The trend is expected to worsen in the future with higher frequency of fire occurrences and longer durations of wildland fire seasons with warmer and earlier springs (Westerling et al., 2006). With limited evidence of forest density preferences of WUI homebuyers, a primary research question remains: How does forest density influence sales value in high fire risk WUI regions, and to what scale? To investigate this question, we applied a spatial hedonic pricing model to a set of high fire risk WUI house sales in four Western regions.

1.1. Literature review: WUI forest density and hedonic pricing

By observing home sale prices in the market, we can discern the preferences of homebuyers for different attributes of homes in aggregate form. The idea of measuring the value of certain implicit characteristics of property, i.e. hedonic pricing, dates back many years. The first application of the hedonic method in residential properties was by Ridker and Henning (1967), where they investigated the association between air quality and property values. Since then, there have been many hedonic studies in urban housing markets that show evidence of negative impacts of poor air quality on housing prices (e.g. see the meta-analysis of more than 160 separate estimates from 37 studies by Smith and Huang, 1993).

However, the influence of tree density on housing prices has been found to be both positive and negative, making results hard to generalize. Although there are many benefits of increasing canopy covers in communities, especially in urban areas, there are also costs, such as increased fire risk, energy costs and water usage (Nowak et al., 2010). Thus, homebuyer preferences for tree density depend on the degree of urbanization in the area (Cho et al., 2008) and the relative scarcity of trees in the neighborhood (Netusil et al., 2010). Natural amenity values of forests can vary spatially and temporally depending on forest-patch size and density (Cho et al., 2009) and can vary based on prevailing ecological, social, and economic conditions (Nowak et al., 2010). Additionally, variations in tree density at the household level can create positive and negative externalities for adjacent land owners and can influence neighbors' efforts at creating defensible space (Shafran, 2008).

Given mixed findings of direction and scale for forest density preferences, we view forest density as a blessing and a curse depending on location-specific and behavioral contexts reflecting home buyers' knowledge, attitude, and preferences. Economists treat environmental amenities, or avoidance of environmental disamenities, as spillover effects that are typically external (externality) to the measurement of total economic trade-offs (Mendelsohn and Olmstead, 2009; Mishan, 1974). Hedonic price models are well suited for determining the amenity or disamenity influence of a perceived attraction or hazard on a particular market segment of home buyers. However, hedonic models assume buyers and sellers have full and accurate information about housing characteristics and that housing markets are mobile enough to reflect current preference or risk (Mendelsohn and Olmstead, 2009).

The assumption of complete information may be particularly problematic for homeowner's perception of wildfire risk and the financial consequences of experiencing a wildfire. Abrams et al. (2015) found a large discrepancy between community fire risks perceived by local homeowners and assessed by fire officials. Mozumder et al. (2009) found positive willingness to pay among WUI residents for updated wildfire risk maps, indicating that residents do not have complete information. Donovan et al. (2007) found no preference for the level of surrounding vegetation density (e.g., high or low) for WUI homeowners outside of Colorado Springs, Colorado, despite finding a decrease in prices after the fire department initiated wildfire risk ratings for individual houses. Champ et al. (2009) surveyed WUI homeowners in the same location and found little consideration (only 27% of WUI homeowners) for wildfire risk when purchasing their house. They also found higher preference for homes closer to “dangerous topography” in terms of wildfire risk (Champ et al., 2009). Similarly, high natural amenity locations are typically correlated with high hazard risk (Loomis, 2004). This suggests that in some areas, the attraction of the wilder natural features that are typically associated with greater wildfire risk outweigh the disamenity, or hazard, represented by wildfire risk.

None of the published hedonic studies were able to separate changes in wildfire risk perception and natural amenities (Venn and Calkin, 2011), as it likely requires the use of survey-based stated preferences methods as opposed to revealed preference methods. There is little information on the role of wildfire risk on homebuyer preferences in fire-prone areas (Champ et al., 2009). Even for homebuyers with some awareness, the full level of risk is poorly defined as many wildfire risk variables are difficult to quantify at the WUI parcel-specific level. Furthermore, homebuyer's risk perceptions in high natural hazard areas have largely been shown to be inaccurate for many natural disasters, including fire, flooding, and earthquakes (Mueller et al., 2009). So in this case, complete information is unknown and homebuyers have incomplete and varied level of risk assumptions. This is complicated by the fact that the federal government assumes much of the fire suppression and management burden, providing a government subsidy to WUI homeowners (Gude et al., 2008; Busby and Albers, 2010). Federal aid and assistance for victims of natural disasters is common practice, but the reactionary nature of federal payments and resources used to help residents in high risk natural areas (e.g., WUI, floodplain, or coast) provides an incentive to locate in hazardous areas (Kim and Hjerpe, 2011). This incentive creates a market failure leading to excessive risk taking by individuals with insurance and federal assistance, generating free-rider effects whose tabs are collectively paid by society (Loomis, 2004; Talberth et al., 2006; Cavallo and Noy, 2009; Busby and Albers, 2010).

The hedonic fire risk literature has largely been focused on empirical *ex post* investigations of wildfires (Huggett, 2004; Loomis, 2004; Mueller and Loomis, 2008; Mueller et al., 2009; Stetler et al., 2010). They have generally found negative associations between housing prices and proximity to a wildfire. A couple exceptions to the *ex post* investigations in the hedonic fire risk literature include investigations of the effects of a wildfire risk rating (Donovan et al., 2007; Champ et al., 2009) and forest density variation for one community (Kim and Wells, 2005). Hedonic studies of other natural disasters, such as hurricanes and floods, showed the effects of recent experience with a disaster on perceived risk and property values (Bin and Polasky, 2004; Morgan, 2007). Although experiences with a disaster tend to increase perceived risk and negatively affect property values, those impacts may be short lived (Atreya et al., 2013). Much less is known about *ex ante* behavior of WUI homebuyers before experiencing a close fire. Preferences for forest density, prior to major fires, as well as the mechanisms through which forest density is processed in home owners' preferences, are in need of further investigation and hold important policy implications for correcting market failures.

2. Methods

We first specified a comprehensive WUI hedonic price model a priori of existing data, and then generated a sampling methodology that would best fit our model specification. Once our hedonic model was fully specified and populated with observational data, we conducted numerous model and regression diagnostics.

2.1. Specifying a WUI hedonic price model

A house can be thought as a package of many characteristics. For example, the price of a house is determined by size, number of rooms, and natural amenities, as well as proximity to business centers or schools. In other words, the ith house price (p_{hi}^{0}) is a function of housing structure vectors (S_i), neighborhood characteristic vectors (N_i), and location-specific environmental amenity vectors (E_i).

$$p_{hi}^{0} = p_h(S_i, N_i, E_i) \quad (1)$$

Previous hedonic price models for WUI houses are limited to a few studies and generally include the traditional explanatory attributes of *S*, *N*, and *E* (e.g., Donovan et al., 2007; Mueller et al., 2009; Stetler et al., 2010). However, our interest was to isolate surrounding forest density as a potentially explanatory attribute in the most at-risk WUI areas. Thus, we incorporate a set of WUI (W) variables that are defined by designation of fire-risk (Interface or Intermix), proximity to fire stations, and forest density levels surrounding WUI homes at two proximities (100 m and 500 m radius circular density buffers). Our hedonic price model is specified as:

$$p_{hi}^{0} = p_h(S_i, N_i, E_i, W_i) \quad (2)$$

or statistically as:

$$\mathbf{P} = c + \boldsymbol{\beta}(\mathbf{X}) + \boldsymbol{\varepsilon} \quad (3)$$

where **P** is the WUI house sales price, c is a vector of constants, **X** is a vector of house characteristics *S*, *N*, *E*, and *W*, $\boldsymbol{\beta}$ is the vector of coefficients, and $\boldsymbol{\varepsilon}$ is a vector of error terms.

Following previous literature (Graves et al., 1988; Palmquist, 1983; Stetler et al., 2010), we have considered a number of structural variables known to be significant in determining the property price, such as lot and living area sizes, total numbers of bedrooms and bathrooms, and age of house at the time of purchase. For neighborhood variables, properties were categorized by census tracts and social-economic information was estimated at census-tract level according to the 2010 US Census. The variables included the WUI city (Flagstaff, Bend, S. Lake Tahoe, and Missoula), income level of the neighborhood, distance to shopping and business centers (downtowns), and buyer location. Overall, the four WUI regions contained 24 individual census tracts. Homebuyer addresses were used to classify all WUI property sales to in-region or out-of-region buyers. Zip codes of homebuyers were cross-examined with Google Earth ecosystem imagery to indicate whether or not the homebuyer was located in a similar dry-mixed conifer and high wildfire risk area. Additional neighborhood variables were explored, such as traditional hedonic variables including education levels, quality of schools, and crime rates. However, our final set of WUI homes was similar enough that there was little variation in these more urban-oriented variables, leading us to keep them out of the model.

Three environmental amenities were included in our hedonic function model—distance of the WUI house to national forest lands,[1] distance to a lake or reservoir, and distance to a perennial river. WUI variables included measures of forest density, WUI designation as either WUI Interface or Intermix, and distance to fire stations. Given findings of past wildfires influencing house sales prices, we considered including recent wildfires as an explanatory WUI variable in our model. However, based on aerial imagery, the four regions have not experienced many recent wildfires within the WUI zones, limiting the representation of this variable. WUI designations were modeled as dummy variables. Forest density was measured in two different sizes of buffers around each housing unit: 100 m radius and 500 m radius. We hypothesized that homeowners' preference for forest density may differ for the immediate surroundings and for the larger vicinity. To control for different regional forest densities and variations in climate and geomorphology that affect each regions' wildfire regime, forest density was classified into three categories for each city: high, medium, and low. The high, medium, and low classification represented even allocation (one-third each) of each region's WUI house forest density percentages. These forest density ranges were entered as dummy variables so they could be combined with other regions so as to observe any relative influence of local forest

Table 1
Description of variables included in the analysis.

Variable name	Definition	Expected sign
Dependent variable: log (adj sale price)	Natural log of sale price of the home in locally time-adjusted markets for Quarter 2, 2013 ($)	
Explanatory variables		
Structural variables (S)		
Log living area (sq. ft)	Natural log of house square footage	+
Bathrooms	Number of bathrooms	+
Bedrooms	Number of bedrooms	+
Log lot area (acreage)	Natural log of lot acreage	+
Year built	Year house was built	?
Neighborhood variables (N)		
WUI City		
Flagstaff, AZ	If sale was in Coconino Co., AZ, dummy = 1	?
Bend, OR	If sale was in Deschutes Co., OR, dummy = 1	?
S. Lake Tahoe, CA	If sale was in El Dorado Co., CA, dummy = 1	?
Missoula, MT	If sale was in Missoula Co., MT, dummy = 1	?
Log income	Natural log of census tract-level median income in $2013	+
sqrt proximity to shopping	Square root of house distance (meters) to city center	−
Buyer location	Dummy variables for In-Region and Out-of-Region buyers	?
Environmental amenity variables (E)		
Log proximity to public forests	Natural log of house distance (meters) to closest USFS boundary	−
Log proximity to water body	Natural log of house distance (meters) to closest lake or reservoir	−
Log proximity to river	Natural log of house distance (meters) to closest perennial river	−
WUI variables (W)		
WUI or WUI-mix	Dummy variables for WUI designation Interface or Intermix	?
Log proximity to fire station	Natural log of house distance (meters) to closest fire station	−
Forest density (100 m)		
Low100	If house's 100 m buffer was Low Forest Density, dummy = 1	?
Medium100	If house's 100 m buffer was Med Forest Density, dummy = 1	?
High100	If house's 100 m buffer was High Forest Density, dummy = 1	?
Forest density (500 m)		
Low500	If house's 500 m buffer was Low Forest Density, dummy = 1	?
Medium500	If house's 500 m buffer was Med Forest Density, dummy = 1	?
High500	If house's 500 m buffer was High Forest Density, dummy = 1	?

[1] Ham et al. (2012) illustrated that the influence of surrounding public lands on house values was dependent on heterogeneity in types of land uses allowed (e.g., motorized vs. non-motorized, resulting noise impacts, etc.). To account for this heterogeneity, we have sampled from multiple WUI areas with similar forest types and land uses.

density in these high fire risk regions. A full description of variables used in our analysis is presented in Table 1.

2.2. Sampling methodology

We obtained sales records of single family residential housing units for four fire-prone WUI regions for multiple years (2011–2014) and carefully selected residential development within the WUI only. Our primary research question was aimed at isolating the potential influence of forest density variation on house values in Western fire-prone forests. To do this, we selected WUI areas with similar forest types, fire regimes, and natural environmental amenities. Market segmentation across locations, geographies, and environmental attributes can be a concern for a combined hedonic price function of multiple regions and needs to be considered and accounted for in econometric analysis. We employed a sampling design that would ensure consistency in both the demand and supply structures of each sub-region (Freeman, 1993) and the subsequent vector of coefficients for each region (Haab and McConnell, 2003), allowing for the estimation of a single hedonic price function.

2.2.1. Study area selection

The four WUI cities selected were: Bend, Oregon, Flagstaff, Arizona, South Lake Tahoe, California and Missoula, MT (see Fig. 1).

These four Western communities have similar degrees of urbanization and economic conditions (See Table 1), and can all be categorized as natural amenity-based towns that include many outdoor recreation and tourism industries and services. All WUI cities are in close proximity to national forest lands and have relatively high percentages of second-home ownership. All four cities also have similar ecological conditions of dry, mixed conifer and have substantial wildfire risk in the surrounding forests. For example, approximately 13,000 houses in Deschutes County, Oregon have been designated as "High" or "Very High" risk for wildfire damage, representing a combined total reconstruction value estimated at more than $3.4 billion (CoreLogic, 2015). As seen in Table 2, all four regions contain numerous houses in the WUI.

2.2.2. Geo-data selection and tabulation

Sales prices and descriptive characteristics for over 20,000 houses from the four Western counties (Coconino, AZ; Deschutes, OR; El Dorado, CA; and Missoula, MT) from 2011 to 2014 were acquired from a real estate firm. Data were cleaned and filtered to remove duplicates, missing data, corrupt or incongruous data, and notable outliers. Geographical coordinates for each parcel centroid were used to display houses in a GIS layer. Numerous manual checks were conducted to make sure the coordinates were accurate at high resolution. We obtained National Agriculture Imagery Program (NAIP) aerial imagery at 1 m ground sample distance (http://www.fsa.usda.gov/programs-and-services/aerial-

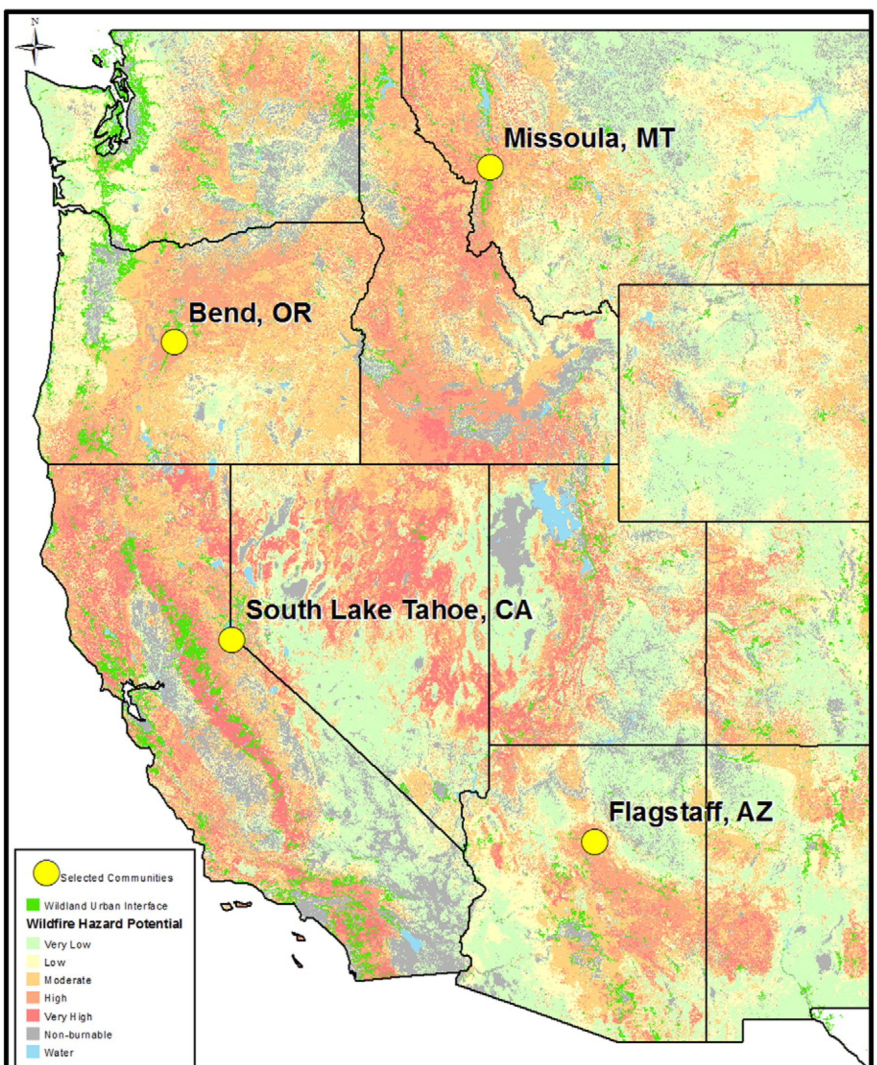

Fig. 1. Selected western dry, mixed-conifer WUI regions.

Table 2
Description of selected WUI cities.

WUI city	Dominant WUI forest type[a]	Population 2013	WUI houses in county[b]	Median income	Median housing price
Flagstaff, AZ	Ponderosa pine woodland	68,700	13,983	$49,800	$266,200
Bend, OR	Ponderosa pine woodland	81,236	17,536	$53,000	$255,800
S. Lake Tahoe, CA	Mesic mixed conifer forest and woodland	21,387	29,504	$41,000	$319,800
Missoula, MT	Dry-mesic montane mixed conifer forest	69,100	6771	$40,700	$237,600

Source: US Census Bureau, State and County Quick Facts: http://quickfacts.census.gov/.
[a] NAIP Land Cover Imagery.
[b] Headwaters Economics at: http://headwaterseconomics.org/dataviz/wui-development-and-wildfire-costs

photography/imagery-programs/naip-imagery/index) and overlaid wildland-urban interface (WUI) GIS layers as defined by Radeloff et al. (2005) and presented by the SILVIS Lab at the University of Wisconsin (http://silvis.forest.wisc.edu/maps/wui_main). The WUI classifications from Radeloff et al. (2005) use the Federal Register 66 (USDA and USDI, 2001) WUI definition and include both Intermix and Interface WUI areas.[2] All houses not designated as either WUI Intermix or Interface (e.g., uninhabited or too low of housing density) were filtered out. Intermix and Interface were then classified as dummy variables. The National Hydrography Data set was used for identifying house distances to lakes, reservoirs, and rivers (http://nhd.usgs.gov/index.html), and Google Earth was used to indentify house distances to fire stations.

Following a stepwise selection process, we mapped city boundaries for each region, implemented a 7.5-mile buffer surrounding the city boundary, and removed all houses from inside the city boundaries. We were left with a doughnut-shaped WUI zone surrounding each city (see Fig. 2). The 7.5-mile outer WUI buffer was clipped to our Land Cover/Forest Area and populated with recently sold houses. Outside of 7.5 miles beyond city boundaries in general, housing density rapidly decreased and became too low compared to our WUI datasets. The WUI buffer was created to separate WUI homes based near popular natural amenity cities from homes in more remote, rural settings. Homogenizing the most at risk WUI homes for each city was our priority as rural homebuyers may exhibit different preferences and demographics than our sample. Finally, through visual observation, we eliminated WUI buffer areas with very low or no vegetation cover, such as open grass lands, water bodies, and golf courses. Additionally, houses located in land cover dominated by other forest types, such as pinyon/juniper, were removed.[3] Final selected WUI houses are illustrated in Fig. 2.

To determine our forest density WUI variables, each transacted property in our WUI region was buffered at two distances. Two circles were drawn around each parcel centroid—one with a 100 m radius (3.14 ha/7.8 acres) and one with a 500 m radius (78.5 ha/194 acres). Background land cover allowed us identify "tree" or "no tree" at a one square meter resolution. Forest density buffers at the 100 and 500 m radius-level were tabulated by totaling tree and no-tree units. With two unique tree percentages for each WUI house, we were able to classify and isolate the influence of forest density in WUI house sales at a broad level and at a more immediate level.

Our data were from a 3 year span from 2011 to 2014. To control for regional market trends and timing, both seasonally and annually, we adjusted all property sales to a common year (2013) and quarter (2). We used quarterly housing price index from the US Federal Housing Finance Agency at the three-digit zip code level.

2.3. Hedonic regression analytics

The hedonic pricing method is a nonmarket valuation technique used to estimate the influence of latent housing characteristics by gauging their individual contribution to overall selling prices. Advancements in hedonic methods have addressed a number of analytical issues concerning spatial dependence, multicollinearity, and interpretation of regression results. Below, we detail our treatment of these hedonic considerations.

2.3.1. Spatial dependence and hedonic regression

Our WUI dataset represents multiple neighborhoods across four disparate regions. While we have included as many potentially influencing variables as possible, there is still a chance that clustering of houses, or their proximity to neighboring houses, may have an influence on their sales price. This spatial dependence was first formally stated by Tobler (1970) and the first law of geography: "everything is related to everything else, but near things are more related than distant things."

Anselin and Bera (1998) define spatial autocorrelation as the coincidence of value similarity with locational similarity. Positive spatial autocorrelation is the clustering in space of similar values, whereas negative spatial autocorrelation describes the dissimilar values associated with different neighborhoods farther out in space. Two types of spatial dependence can occur. Spatial lag refers to spatial dependencies across observations of the dependent variable, while spatial autocorrelation refers to dependence across error terms. Maximum likelihood is a common technique used for spatial estimation.

Mueller and Loomis (2008) analyzed effects of correcting for spatial dependence in hedonic property models examining amenities and disamenities of natural hazards and a wildfire risk model. Their findings showed small differences between modeled spatial dependence and spatially uncorrected OLS estimates, but highlight that the small differences can have serious implications for final interpretations and implicit prices. Donovan et al.'s (2007) WUI hedonic model, however, did find large differences for estimated coefficients in spatially corrected regressions versus uncorrected OLS regressions. Given the numerous findings of spatial dependence in hedonic price functions, we investigated this issue in our dataset and addressed the problem in our final regression models.

Because spatial data typically violate the assumption of observation independence required by ordinary regression methods (Anselin and Bera, 1998; LeSage, 2014), we analyzed our data in multiple spatial models. Our motivation for accounting for spatial dependence was to limit potential omitted variable bias by estimating the spatial effects of house clusters (neighborhoods) within each region and to account for potential house price association with neighbors (e.g., Anselin and Bera, 1998, LeSage and Pace, 2009). Individual houses receive and exert influence on other neighbors just by being in close proximity to each other (e.g., selling values are often comprised of average surrounding selling prices) — a focus of the spatial lag function. We also hypothesize that there may be other explanatory variables (characteristics)

[2] Intermix and Interface definitions from the SILVIS Lab documentation: "*The Wildland-Urban Interface* (*WUI*) is composed of both interface and intermix communities. In both interface and intermix communities, housing must meet or exceed a minimum density of one structure per 40 acres (16 ha). Intermix communities are places where housing and vegetation intermingle. In Intermix, wildland vegetation is continuous, more than 50% vegetation, in areas with more than 1 house per 16 ha. Interface communities are areas with housing in the vicinity of contiguous vegetation. Interface areas have more than 1 house per 40 acres, have less than 50% vegetation, and are within 1.5 mi of an area (made up of one or more contiguous Census blocks) over 1325 acres (500 ha) that is more than 75% vegetated. The minimum size limit ensures that areas surrounding small urban parks are not classified as interface WUI."

[3] Pinyon pine/juniper forests occur in only two of our four regions and houses located in pinyon/juniper were generally of lower value when compared to the primary ponderosa and dry-mixed conifers forests of the WUI. Due to these differences, we excluded house sales in pinyon/juniper forests to focus on a more homogenous set of WUI homes.

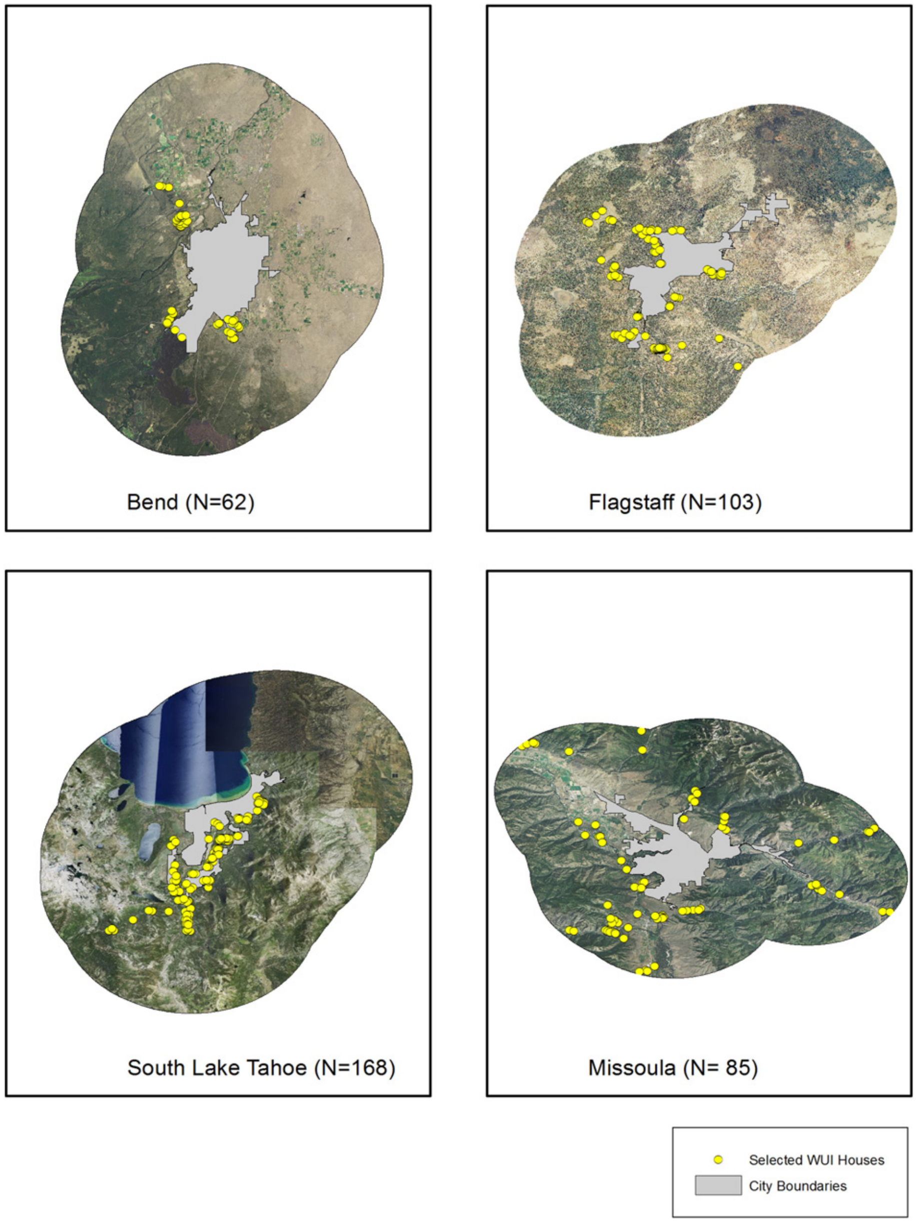

Fig. 2. Final selected properties for WUI cities ($N = 418$).

shared by certain neighbors that we were unable to isolate in our overall model specification. These shared characteristics could be a road, a unique natural feature, or a particular school that could lead to spatial autocorrelation among the error terms of WUI house price estimations. These unknown variables may have an influence on home prices of houses spatially clustered around them, indicating the need for a spatial error model.

Estimating spatial models requires the construction of a spatial weights matrix that can be applied to our final functional form in Eq. (3) to estimate spatial lag, spatial error, and combinations of the two (e.g., Durbin or mixed). Spatial dependencies across the dependent variable result in a spatially lagged model. The specified model for spatial lag becomes:

$$\mathbf{P} = \rho \mathbf{W}_1 \mathbf{P} + \beta X + \boldsymbol{\varepsilon}, \tag{4}$$

where $\mathbf{P}$ is a vector of house selling Prices, $\mathbf{X}$ is vector of house characteristics, β is a vector of characteristic coefficients, and $\boldsymbol{\varepsilon}$ is a vector of the i.i.d error term. $\mathbf{W_1}$ is an $N \times N$ spatial weighting matrix describing the spatial lag process, and $\boldsymbol{\rho}$ is the scalar spatial lag coefficient (Donovan et al., 2007).

If individual error terms of WUI house prices are spatially autocorrelated, spatial error dependence will be present. The spatial error model can be represented as:

$$\mathrm{P} = \beta\mathbf{X} + \boldsymbol{\varepsilon}, \text{ where } \boldsymbol{\varepsilon} = \boldsymbol{\lambda}\mathbf{W}_2\boldsymbol{\varepsilon} + \mu, \tag{5}$$

where $\mathbf{P}$, $\mathbf{X}$, and β are the same vectors of house price, characteristics, and coefficients. However, in the spatial error model, $\boldsymbol{\varepsilon}$ represents a combined error term that has a spatially weighted matrix ($\mathbf{W_2}$) applied to the error terms, $\boldsymbol{\lambda}$ is the scalar spatial error coefficient, and $\boldsymbol{\mu}$ is a vector of the error term (Elhorst, 2014).

With two broad categories of spatial dependence, lag and error, and sub categories representing the various manners in which they manifest (i.e., exhibited on dependent variable, independent variables, and/or error term), there are multiple spatial models that provide for combined lag and/or error spatial dependence estimates. Two popular models are the spatial mixed model (or SAC) and the spatial Durbin model. The spatial mixed model allows for lag and error autocorrelation and can be represented as:

$$\mathbf{P} = \rho\mathbf{W}_1\mathbf{P} + \beta\mathbf{X} + \boldsymbol{\varepsilon}, \text{ where } \boldsymbol{\varepsilon} = \boldsymbol{\lambda}\mathbf{W}_2\boldsymbol{\varepsilon} + \boldsymbol{\mu}, \tag{6}$$

where matrix $\mathbf{W_1}$ may be set equal to $\mathbf{W_2}$, and the vectors are the same as in Eqs. (4) and (5) (LeSage and Pace, 2009). The spatial Durbin model, on the other hand, allows for spatial lags of the dependent variable *and* the explanatory variables, or:

$$\mathbf{P} = \rho\mathbf{W}_1\mathbf{P} + \beta\mathbf{X} + \mathbf{W}_1\mathbf{X}\theta + \boldsymbol{\varepsilon}, \tag{7}$$

where the new addition, $\mathbf{W_1X}\theta$, represents the exogenous interaction effects among the independent variables (Elhorst, 2014).

2.3.2. Regression diagnostics

Variables were observed in scatterplots, histograms, and kernel density plots to investigate normality and heteroskedasticity. Our dependent variable exhibited non-normal probability distributions, being skewed to the right. Numeric and visual transformation tests in STATA showed that a logarithmic transformation worked the best in reducing skewness and kurtosis for the property values (smallest chi-square), and more importantly for their residuals. There is little guidance on functional form for hedonic property models (Taylor, 2003; Mueller and Loomis, 2008; Hussain et al., 2013) and logarithmic transformation of our dependent variable is consistent with previous research. Based on data exploration, seven independent variables were transformed to log and one was estimated as a square root function. Interaction effects among primary explanatory variables and the four sub-markets illustrated similar preference structure of attributes on the demand side, though some interaction coefficients indicate that supply structures are not exact matches among sub-markets. Further analysis showed that regional WUI houses were more similar to WUI houses in other regions, in terms of attributes, than when compared to houses found in adjacent city limits. Finding homogeneity among the four WUI housing markets provided confidence that inclusion of regional dummies generated appropriate intercept shifts so as to estimate a single hedonic price function.

Summary statistics and basic correlations were investigated and a set of diagnostic tests were used to determine if multicollinearity or heteroskedasticity remained problems. A White's Test on heteroskedasticity led us to use Huber-White robust standard errors in our final analysis. Multicollinearity is especially problematic for hedonic pricing models, given the inclusion of similar yet distinct housing attributes such as the number of bathrooms and the number of bedrooms (Hussain et al., 2013). While some degree of multicollinearity will always be present (Stewart, 2005), we employed various testing of the degree and scale of correlation among our hedonic pricing attributes to help estimate the most relevant model specification. Variance inflation factors (VIF) for all variables were determined, along with overall model condition numbers. These diagnostics led to the removal of four variables from our final model specification due to high correlations with other variables: bedrooms, year built, income, and distance to river. Our final model estimated had a condition number of 17.02, which is in the optimal range between 10 and 30 as suggested by Gujarati (1998).

A Moran's I Test indicated the presence of spatial autocorrelation in our communities ($p = 0.000$), requiring the use of spatial error and lag models. A spatial weights matrix and eigenvalue vectors were generated and applied to our spatial regression. We used an inverse-distance spatial weights matrix as recommended by Mueller and Loomis (2008). Sensitivity analysis of varying band distances revealed robust results largely insensitive to neighbor distance delineations. Under our spatial weights matrix, parcels across regions are not considered neighbors. Our distance band used was 3 km. The diagonal elements are zeroes while the off diagonal elements are the weighted average of the particular neighborhood, where rows sum to one. At less than 3 km, we began to see a few islands (houses with no neighbors) and a sparse matrix.

Prior to spatial regressions, spatially uncorrected OLS regressions were estimated and retained for comparison. Estimate statistics such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were tabulated and used for guidance on preferred models. Initial OLS regressions were estimated as generalized linear models (GLM) so as to obtain comparison criteria to our spatial regressions. Based on maximum likelihood estimates, and AIC and BIC stats, the spatial regressions were shown to be a superior fit for our data over the spatially uncorrected OLS regression.

The Moran's I Test provided for a first view of spatial dependence in our sample. To get more details on the nature of the spatial dependency in our communities, we estimated robust Lagrange Multipliers (LM) for the weights matrix after an OLS specification. Starting with a non-spatial linear regression and then investigating whether or not to move to a spatial regression is known as the specific-to-general approach (Elhorst, 2014). The robust LMs indicated that the spatial lag process was likely present in our sample ($p = 0.051$), but that spatial error process might not be present ($p = 0.228$). We continued to estimate four spatial models: the lag, error, Durbin, and mixed (see Eqs. (4)-(7)). However, as indicated by the robust LM tests, the spatial lag model was ultimately the best specification.

The four spatial models were estimated using maximum likelihood and evaluated based on the following model selection criteria: significance of rho and lambda (the scalar coefficients for lag and error process), log likelihood function, the AIC, and the BIC. The individual spatial dependence models, lag and error, were better specified than the combination spatial models and we present the criteria estimates for the lag and error models in Table 4. Of the spatial lag and error models, the lag model had the lower AIC and BIC and the larger log likelihood estimate.

Both the lag and error models yielded a significant rho estimate ($p = 0.053$) and lambda estimate ($p = 0.059$). In the combined spatial models (Durbin and mixed) however, neither individual rho nor lambda were significant, and the AIC and BIC estimates were substantially larger. The log likelihood estimates are not as comparable across the four spatial models due to different degrees of freedom, as the combined spatial models have interaction parameters along with the explanatory variables. AIC and BIC incorporate penalties for greater model parameters, whereas the log likelihood function does not (Stewart, 2005). As a result, AIC and BIC are better suited for evaluating the specification of multiple spatial models. Based on specification tests for four spatial models of our data, the spatial lag model is preferred, with the spatial error model being next preferred.

2.3.3. Regression interpretation: implicit prices

The hedonic pricing method is a nonmarket valuation technique that allows for the estimation of preferences for nonmarket attributes such as forest density on housing prices. Partial derivatives of the attributes are obtained and can be interpreted as implicit marginal prices for those attributes. That is, the hedonic regression coefficients of attributes measure the rate of change in house price with respect to a one unit change in the attribute. These coefficients can be used to infer households' WTP for marginal changes in the level of WUI house attributes—and is why they are termed implicit prices (Loomis, 2004).

Evaluation of attributes in a linear hedonic model is straightforward, where attribute coefficients represent the dollar increase or decrease in home selling value associated with an additional unit of the attribute. In transformed functional models, such as the semilog model, coefficients of attributes typically represent elasticities, where coefficients are a percentage that is applied to the house value. Interpretation of dummy variable coefficients, however, is a bit more nuanced because they represent relatively large changes in the dependent variable.

To interpret our regression coefficients, we incorporate interpretive expressions for our semilog model illustrated by Kennedy (1981) and Stewart (2005) and applied to a hedonic price function by Hussain et al. (2013). Specifically, the implicit price expression used for continuous, non-transformed explanatory variables is:

$$IMP_{Bathrooms} = \beta_1 * AdjSalesPrice. \tag{8}$$

For explanatory variables measured in logarithms:

$$IMP_{LivingArea} = \beta_1 \left(\frac{AdjSalesPrice}{LivingArea} \right). \tag{9}$$

But, for discrete explanatory variables such as dummies, treating attribute coefficients as direct elasticities as done above results in a heavily biased estimator (Stewart, 2005). This is because a large absolute change in binary variables (e.g., going from high, to medium, to low forest density) represents a relatively large change in our dependent variable (WUI house sale price); whereas applying coefficients directly as done in the case of continuous variables captures smaller changes at a finer scale, resulting in less biased estimators. Thus, we use Kennedy's (1981) estimator to reduce bias for interpreting our WUI dummy variables:

$$IMP_{ForestDensity} = \left[\exp\left(\beta_1 - 0.5 s^2_{\beta_1}\right) - 1 \right] AdjSalesPrice, \tag{10}$$

where s is the standard error of the *ForestDensity* dummy variable.

Additionally, a spatial multiplier may exist when local spillover effects result in further neighborhood house price adjustments. Spillover effects can be incorporated into the model resulting in a set of indirect effects. Indirect effects occur when neighboring house values influence the observed house sales price in that neighborhood, as is often the case with real estate markets. So beyond the direct effects of spatially corrected regression coefficients calculated above in Eqs. (8)-(10), there may be indirect spatial spillover effects that need to be interpreted for final marginal implicit price calculations. Kim et al. (2003) define the spatial multiplier as the sum of each row of the inverse matrix of row-standardized spatial weights, or $1 / (1 - \boldsymbol{\rho})$, if a unit change were induced at every location. Adding this to Eq. (8), we have a final implicit price expression of:

$$IMP_{Bathrooms} = \beta_1 * AdjSalesPrice * \left\{ \frac{1}{1-\boldsymbol{\rho}} \right\}, \tag{11}$$

where the scalar parameter $\boldsymbol{\rho}$ is the coefficient for the spatial lag process.

The spatial error model does not allow for the estimation of indirect, or spillover, effects. Our Eq. (11) illustrates an implicit price estimation adjustment when using the spatial lag model or the spatial mixed model (SAC). Elhorst (2014) illustrates that the ratio of spillover effects to direct effects under the lag and mixed models is the same for every explanatory variable, meaning that one general spatial multiplier is applied to all variables. In many cases however, each explanatory variable may have a unique spatial multiplier that can be difficult to isolate. For advanced interpretation of spatial multipliers for numerous spatial specifications see LeSage and Pace (2009) and Elhorst (2014).

3. Results

After the spatial delineation described in Section 2.2.2, we had 418 property sales records from four communities. Table 3 shows summary statistics for the dependent and independent variables in our model. Our dependent variable is the log of adjusted home sale prices. Average home sale prices in our sample was $358,380 in adjusted 2013 prices, which is higher than the average prices of all four cities where the study sites are located. Higher house values can be explained by the fact that residential properties built in WUI areas tend to be quite a bit larger than those in urban centers (averaging 2100 sq. ft., or 195 sq. m. in our dataset), and are located on much larger parcel sizes (mean WUI lot size was 1.3 acres, or 0.53 ha. in our dataset).

Table 3
Descriptive statistics for dry, mixed conifer WUI houses ($N = 418$).

Variable	Mean	Std. dev.	Min	Max
Dependent variable				
Adjusted sale price: $2013, regionally-adjusted	358,380	205,108.1	60,507	1,618,750
Explanatory variables				
Structural variables (S)				
Living area (sq. ft)	2116.041	940.766	469	6591
Bathrooms	2.469	1.030	1	6
Bedrooms	3.232	0.962	1	8
Lot area (acres)	1.384	2.737	0.013	25.050
Year built	1986.031	15.617	1926	2013
Neighborhood variables (N)				
WUI City				
Flagstaff, AZ	0.246	NA	0	1
Bend, OR	0.148	NA	0	1
S. Lake Tahoe, CA	0.401	NA	0	1
Missoula, MT	0.203	NA	0	1
Income ($)	59,534.26	10,221.38	35,398	86,211
Proximity to shopping (meters)	9013.7	5059.8	1295.1	28,612.6
Buyer location				
Out-of-region	0.423	NA	0	1
In region	0.576	NA	0	1
Environmental amenity variables (E)				
Proximity to public forests (meters)	824.5	1249.4	0.144	5750.8
Proximity to water body (meters)	5983.1	5740.2	22.6	28,605.1
Proximity to river (meters)	20,135.0	21,405.6	0.156	59,615.9
WUI Variables (W)				
WUI or WUI-mix				
Intermix	0.645	NA	0	1
Interface	0.354	NA	0	1
Proximity to fire station (meters)	5050.0	4342.5	146.3	25,311.9
Forest density (100 m)				
Low100	0.330	NA	0	1
Medium100	0.339	NA	0	1
High100	0.330	NA	0	1
Forest density (500 m)				
Low500	0.330	NA	0	1
Medium500	0.339	NA	0	1
High500	0.330	NA	0	1

We present the results from both the spatial error and lag models in Table 4. However, with lower AIC and BIC estimates and a higher log-likelihood statistic (closer to zero), we focus our presentation of results in the text on the spatial lag model. Some of the results followed our general expectation. For example, larger houses with more bathrooms were sold at higher prices. Housing prices tend to be higher in the WUI area in California than places in other states. However, a few descriptor variables such as proximity to shopping, buyer location, proximity to public forests, WUI designation (Interface or Intermix), and distance to fire station were not significant.

One of the most important findings was that forest density preferences of home owners vary for different buffer sizes. At more immediate proximity (100 m buffer) and holding all other attributes constant, we find that WUI homebuyers prefer low forest density in close vicinity of a house (100 m buffer). Specifically, results of our spatial lag model show a $37,910 decrease ($p = 0.006$) in WUI house value when moving from low forest density to medium forest density at the 100 m buffer level, and a $26,499 decrease ($p = 0.060$) when comparing low to high forest density. The interpreted implicit prices illustrate a convex demand function where the price decrease is greatest between low and medium density (see Fig. 3).

At the 500 m forest density buffer however, higher density was preferred. Results indicate a $29,529 decrease ($p = 0.044$) when moving from high to low forest density, and a $25,573 decrease ($p = 0.053$) in WUI home value when comparing high forest density to medium and

Table 4
Spatial regression estimates for dry, mixed conifer WUI houses.

	Spatial error model[a]				Spatial lag model[a]			
	Coef.	Robust std. err.	P > |z|	Implicit price ($)[b]	Coef.	Robust std. err.	P > |z|	Implicit price ($)[b]
Structural variables (S)								
Log living area (sq. ft)*	0.6630	0.0692	0.000	112.3	0.6633	0.0692	0.000	112.3
Bathrooms*	0.1218	0.0303	0.000	43,651	0.1218	0.0302	0.000	43,651
Log lot area (acreage)***	0.0392	0.0230	0.088	10,145	0.0396	0.0230	0.086	10,249
Neighborhood variables (N)								
WUI City (base S. Lake Tahoe, CA)								
Flagstaff, AZ*	−0.1894	0.0621	0.002	−62,408	−0.1911	0.0627	0.002	−62,922
Bend, OR*	−0.3146	0.0645	0.000	−97,277	−0.3153	0.0650	0.000	−97,468
Missoula, MT*	−0.3826	0.0938	0.000	−115,007	−0.3829	0.0943	0.000	−115,092
sqrt proximity to shopping (m)	−0.0009	0.0014	0.525		−0.0009	0.0014	0.509	
Buyer location (base in region)								
Out-of-region	0.0076	0.0387	0.844		0.0080	0.0387	0.837	
Environ. amenity variables (E)								
log proximity to public forests (m)	0.0041	0.0126	0.744		0.0040	0.0127	0.751	
log proximity to water body (m)	−0.0357	0.0237	0.133		−0.0359	0.0238	0.131	
WUI variables (W)								
WUI or WUI-mix (base Interface)								
Intermix	−0.0610	0.0366	0.661		−0.0156	0.0366	0.670	
Log proximity to fire station (m)	−0.0079	0.0369	0.830		−0.0078	0.0371	0.834	
Forest density 100 m (baseLow100)								
Medium100*	−0.1114	0.0401	0.005	−38,038	−0.1110	0.0401	0.006	−37,910
High100***	−0.0764	0.0404	0.058	−26,631	−0.0760	0.0404	0.060	−26,499
Forest density 500 m (base High500)								
Low500**	−0.0855	0.0424	0.044	−29,664	−0.0851	0.0424	0.045	−29,532
Medium500	−0.0631	0.0409	0.123		−0.0631	0.0409	0.123	
Model statistics								
Number of observations	418				418			
Lambda (λ)***	−0.00012		0.059					
Rho (ρ)***					−0.00007		0.053	
Variance ratio	0.634				0.642			
AIC	300.30				300.27			
BIC	376.97				376.95			
Log-likelihood	−131.15				−131.13			
robust Lagrange Multiplier	1.456		0.228		3.809		0.051	

[a] Inverse distance band (0 3) used for spatial weights matrix.
[b] Implicit prices represent the amount an additional attribute contributes to overall price, while holding all other attributes constant. Only significant variables are calculated.
* Statistical significance for both models at the 99% level.
** Statistical significance for both models at the 95% level.
*** Statistical significance for both models at the 90% level.

low densities combined. The difference of moving from high forest density to medium forest density for the 500 m buffer was barely insignificant ($p = 0.123$), with a smaller coefficient than comparing high to low density. In this case, implicit prices illustrate a flatter decreasing demand function for broad level forest density preference in the WUI when comparing high, medium, and low forest densities.

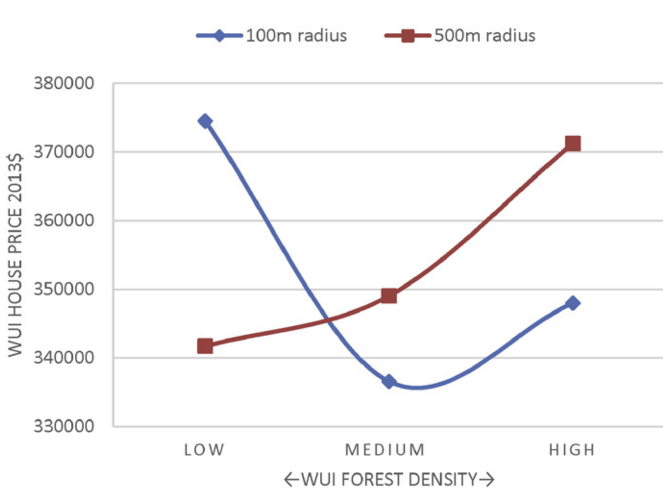

Fig. 3. Implicit demand curves for WUI forest density levels.

4. Discussion

For western dry-mixed conifer WUI regions of the U.S., we see that forest density in close proximity to WUI homes (100 m radius) is negatively associated with house values, as denser forests are realized as a net disamenity. Expanding a WUI property's forest density buffer out to the 500 m radius-level, however, shows a positive association with proximate forest density, being realized as a net amenity. The conflicting scales of WUI homebuyer preferences illustrate the push and pull effects of forests surrounding the examined natural amenity cities.

In surveys of WUI residents, Brenkert–Smith et al. (2006) noted confliction among residents concerning the tradeoffs associated with maintaining certain aesthetics and views as compared to reducing or increasing forest density of individual properties. While it is difficult to dis-entangle amenity and view effects related to forests from effects associated with fire risk perception, it is likely that fire risk is being capitalized into WUI homebuyer preferences. Our study shows that forest density is figured into homeowners' preference in different ways depending on the location, which has important policy implications. Knowing these preferences can help identify home owners most in need of wildfire information and awareness programs, can identify regions where cost-sharing of fire management funds might be most optimal, and can be tracked over time to determine trends.

Assuming that wildfire risk perceptions of WUI homebuyers are partially responsible for the preference associated with varying forest density, we consider a few explanations. First, the preference for lower density forests in the immediate vicinity of homes (100 m) suggests that western WUI homebuyers are concerned with the immediate fire risk surrounding their properties. The number of structures burned by wildfires has been increasing from an average of 209 structures per year lost to wildfire in the 1960's to 2726 structures per year in the 2000's (insurance claims for structure losses in the WUI averaged $800 million/year) (ICC, 2008). Existing WUI homeowners have more awareness and incentives to reduce fuels on their properties. Preference for lower density forests immediately surrounding WUI homes represents a market signal that wildfire risk is being considered for these communities, which is notable given that 42% of sampled WUI house sales were purchased by out-of-region and potential second-home buyers. New arrivals to high risk WUI regions has been a commonly investigated theme, being offered as contributing factor to incomplete and underestimated fire risk information (Paveglio et al., 2015). In separate correlation tests, we found no significant association between in-region and out-of-region WUI homebuyers and forest density levels; nor was there an association between new migrants and WUI house sales price.

At the broader context however, we see that WUI homebuyers prefer to be close to higher forest density and higher wildfire risk areas. Demand for higher forest density can be explained by personal preferences for living in more remote areas with classic natural amenities such as public forests and “dangerous topography” (Champ et al., 2009). Our results implied homeowners only value low density in their immediate vicinity, which may be due to partial evaluation of their risk. Real estate and insurance industries are now urged to recognize property losses due to wildfires caused by windblown embers and pay attention to risk in larger landscapes (CoreLogic, 2015). With rapidly increasing fire risk in these areas, and rapid expansion of WUI house development, we believe that two forms of market failure are likely influencing forest densities net amenity status at the broader level.

Missing and incomplete information concerning the level of wildfire risk is the first form of market failure. Many WUI homebuyers are simply not fully aware of the accompanying wildfire risk and are willing to pay for more information (Mozumder et al., 2009). Donovan et al.'s (2007) findings of changed house prices based on a parcel-level wildfire risk rating conducted by the municipality suggests that information and awareness campaigns can be effective in changing the homebuyer's financial accounting of wildfire risk. As wildfire risk awareness increases, market failures due to incomplete information should decrease.

The second form of market failure stems from federal and municipal subsidies in the form of fire suppression and response, along with insurance premiums that do not fully reflect the natural disaster risk.[4] These market failures provide incentives for WUI expansion and have shifted the burden of fire management in the WUI to the public. WUI residents, on the other hand, are receiving partial free-rider effects because they are not fully responsible for their decisions to locate in fire-prone forests. The results of our empirical analysis are in line with the findings from a game theoretic model by Busby and Albers (2010). They concluded that public liability to protect private values in mixed ownership areas like the WUI essentially encourages private landowners to do too little fuel treatments. Similar to how suppressing fire today increases fire suppression need in the future, assistance and replacement values from both federal policies and insurance during and after wildfires creates greater WUI expansion and protection needs in the future and thus, ever increasing taxpayer-funded fire management.

5. Conclusions and policy recommendations

Evidence that variation in forest density influences house sales prices in the most at-risk western WUI areas is critical and novel information that should be incorporated in the larger calculus of developing broader wildfire management policies. Our findings suggest the need to reconsider broad approaches in awareness campaigns (e.g., Firewise communities), community wildfire protection plans (CWPP), regional development polices, and preventive versus reactionary fire management strategies. For example, fuel reduction treatments are a primary policy mechanism for decreasing wildfire threats and our results indicate that parcel-level defensible space creation and immediately adjacent fuel reduction efforts may increase WUI home values. However, preference for higher density forests implies that if left to homeowners, fuel treatments in adjacent public spaces may be underinvested and may be opposed by a portion of WUI homeowners. Larger or more aggressive publicly funded fuel treatments may have a reducing effect on WUI house values in the short run and may exacerbate existing market failures by providing further subsidies and incentives to WUI homebuyers.

The preference for high forest density in WUI areas at the larger scale (500 m radius-level) may be the result of incomplete information that does not accurately reflect the wildfire hazard. Recommendations for reducing these market failures and shifting the burden of wildfire risk to the WUI homebuyer include greater accounting of societal costs and benefits of wildfire management, greater education and outreach efforts concerning wildfire risk and mitigation, and greater coordination among federal, state, county, and local governments when considering their development policies within high fire risk areas. Often, local policy can influence the direction of WUI development.

We recommend further research on who pays for wildfire management and who benefits from it. Research should include close examinations of economic incentives and disincentives created by wildfire insurance, local wildfire management and education, and federal wildfire management policies. For forest density in the American West, greater sampling of additional communities and homes would provide for more robust estimation. Increased collection of parcel characteristics that comprise fire risk and avoidance such as building/roof materials and slope may identify important variables. Further research on separating the implicit values of view and amenity effects related to forest density from fire risk perception is also needed. For example, stated preference techniques could be used to survey the same sample used in our revealed preference study and comparisons could be made between revealed and stated forest density preferences, along with being able to directly interpret reasons and drivers for density preferences.

Likewise, there is a need to understand WUI homebuyer behavior and preference in the very rural and forested communities. We restricted our sample of WUI cities to natural amenity towns greater than 20,000 people so as to boost our sample size. As such, our findings should not be generalized to the small communities and isolated houses far from any communities. Additional research is needed on these fire-prone property owners, as they likely represent a large share of the wildland fire management responsibility and may behave differently. For example, people living in very dense forests in at-risk hinterlands may prefer low density openings due to their scarcity in their region. They may also have very different budgets and different housing characteristic preferences from those in our study, along with different local development and fire policies.

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[4] Despite the fact that in some high fire risk areas insurance providers are beginning to require some averting activities as a condition of insurance coverage (Talberth et al., 2006).

References

Abrams, J.B., Knapp, M., Paveglio, T.B., Ellison, A., Moseley, C., Nielsen-Pincus, M., Carroll, M.S., 2015. Re-envisioning community-wildfire relations in the US West as adaptive governance. Ecol. Soc. 20 (3), 34.

Abt, K.L., Prestemon, J.P., Gebert, K.M., 2009. Wildfire suppression cost forecasts for the US Forest Service. J. For. 107 (4), 173–178.

Anselin, L., Bera, A.K., 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. Handbook of Applied Economic Statistics, pp. 237–290.

Atreya, A., Ferreira, S., Kriesel, W., 2013. Forgetting the flood? An analysis of the flood risk discount over time. Land Econ. 89 (4), 577–596.

Bin, O., Polasky, S., 2004. Effects of flood hazards on property values: evidence before and after Hurricane Floyd. Land Econ. 80 (4), 490–500.

Brenkert–Smith, H., Champ, P.A., Flores, N., 2006. Insights into wildfire mitigation decisions among wildland–urban interface residents. Soc. Nat. Resour. 19 (8), 759–768.

Busby, G., Albers, H.J., 2010. Wildfire risk management on a landscape with public and private ownership: who pays for protection? Environ. Manag. 45 (2), 296–310.

Calkin, D.E., Gebert, K., 2006. Modeling fuel treatment costs on Forest Service Lands in the Western United States. West. J. Appl. For. 21, 217–221.

Cavallo, E.A., Noy, I., 2009. The Economics of Natural Disasters: A Survey. IDB Working Paper No. 35 (Available at http://dx.doi.org/10.2139/ssrn.1817217).

Champ, P.A., Donovan, G.H., Barth, C.M., 2009. Homebuyers and wildfire risk: a Colorado Springs case study. Soc. Nat. Resour. 23 (1), 58–70.

Cho, S.H., Poudyal, N.C., Roberts, R.K., 2008. Spatial analysis of the amenity value of green open space. Ecol. Econ. 66 (2), 403–416.

Cho, S.H., Kim, S.G., Roberts, R.K., Jung, S., 2009. Amenity values of spatial configurations of forest landscapes over space and time in the Southern Appalachian highlands. Ecol. Econ. 68 (10), 2646–2657.

CoreLogic, 2015. Wildfire Hazard Risk Report: Residential Wildfire Exposure Estimates for the Western United States. CoreLogic (Available at http://corelogic.com).

Covington, W.W., 2000. Helping western forests heal. Nature 408 (6809), 135–136.

Darques, R., 2015. Mediterranean cities under fire. A critical approach to the wildland-urban interface. Appl. Geogr. 59, 10–21.

Donovan, G.H., Champ, P.A., Butry, D.T., 2007. Wildfire risk and housing prices: a case study from Colorado Springs. Land Econ. 83 (2), 217–233.

Elhorst, J.P., 2014. Spatial Econometrics: From Cross-Sectional Data to Spatial Panels. Springer, New York.

Freeman, A.M.I.I.I., 1993. The Measurement of Environmental and Resource Values. Resources for the future, Washington, DC:, pp. 367–420.

GAO, 2009a. Wildland Fire Management: Federal Agencies Have Taken Important Steps forward, but Additional, Strategic Action Is Needed to Capitalize on those Steps. GAO-09-877.

GAO, 2009b. Wildland Fire Management: Actions by Federal Agencies and Congress could Mitigate Rising Fire Costs and their Effects on Other Agency Programs. GAO-09-444T.

GAO, 2015. Forest Restoration: Adjusting Agencies' Information-Sharing Strategies could Benefit Landscape-Scale Projects. GAO-15-398.

Gebert, K.M., Calkin, D.E., Yoder, J., 2007. Estimating suppression expenditures for individual large wildland fires. West. J. Appl. For. 22 (3), 188–196.

Goemans, M., Ballamingie, P., 2013. Forest as hazard, forest as victim: community perspectives and disaster mitigation in the aftermath of Kelowna's 2003 wildfires. Can. Geogr. Geogr. Can 57, 56–71.

Graves, P., Murdoch, J.C., Thayer, M.A., Waldman, D., 1988. The robustness of hedonic price estimation: urban air quality. Land Econ. 84 (3), 220–233.

Gude, P., Rasker, R., Van den Noort, J., 2008. Potential for future development on fire-prone lands. J. For. 106 (4), 198–205.

Gujarati, D.N., 1998. Basic Econometrics. McGraw-Hill Publishing, New York.

Haab, T., McConnell, K., 2003. The Econometrics of Non-Market Valuation. Edward Elgar Publishing.

Ham, C., Champ, P.A., Loomis, J.B., Reich, R.M., 2012. Accounting for heterogeneity of public lands in hedonic property models. Land Econ. 88 (3), 444–456.

Hansen, W.D., Mueller, J.M., Naughton, H.T., 2014. Wildfire in hedonic property models. West. Econ. Forum 13 (1), 23–35.

Huggett Jr., R.J., 2004. Fire in the Wildland-Urban Interface: An Examination of the Effects of Wildfire on Residential Property Markets (PhD Dissertation) North Carolina State University (136 pp.).

Hussain, A., Munn, I.A., Brashier, J., Jones, W.D., Henderson, J.E., 2013. Capitalization of hunting lease income into northern Mississippi forestland values. Land Econ. 89 (1), 137–153.

ICC, 2008. The Blue Ribbon Panel Report on Wildland Urban Interface Fire. International Code Council Headquarters, Washington, DC (Available at http://www.iccsafe.org/government/blueribbon/index.html).

Keeley, J.E., Fotheringham, C.J., Morais, M., 1999. Reexamining fire suppression impacts on brushland fire regimes. Science 284 (5421), 1829–1832.

Kennedy, P.E., 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. Am. Econ. Rev. 71, 4.

Kim, Y.S., Hjerpe, E.E., 2011. Merging Economics and Ecology in Ecological Restoration. In: Egan, D., Hjerpe, E., Abrams, J. (Eds.), Human Dimensions of Ecological Restoration. Island Press/Center for Resource Economics, pp. 191–206.

Kim, Y.-S., Wells, A., 2005. The impact of Forest density on property values. J. For. 103 (156-151).

Kim, C.W., Phipps, T.T., Anselin, L., 2003. Measuring the benefits of air quality improvement: a spatial hedonic approach. J. Environ. Econ. Manag. 45 (1), 24–39.

LeSage, J.P., 2014. What Regional Scientists Need to Know about Spatial Econometrics. (Available at *SSRN* 2420725).

LeSage, J.P., Pace, R.K., 2009. Introduction to Spatial Econometrics. Chapman &Hall/CRC, Boca Raton, FL.

Liang, J., Calkin, D.E., Gebert, K.M., Venn, T.J., Silverstein, R.P., 2008. Factors influencing large wildland fire suppression expenditures. Int. J. Wildland Fire 17, 650–659.

Loomis, J., 2004. Do nearby forest fires cause a reduction in residential property values? J. For. Econ. 10 (3), 149–157.

McFarlane, B.L., McGee, T.K., Faulkner, H., 2011. Complexity of homeowner wildfire risk mitigation: an integration of hazard theories. Int. J. Wildland Fire 20, 921–931.

Mell, W.E., Manzello, S.L., Maranghides, A., Butry, D., Rehm, R.G., 2010. The wildland–urban interface fire problem–current approaches and research needs. Int. J. Wildland Fire 19 (2), 238–251.

Mendelsohn, R., Olmstead, S., 2009. The economic valuation of environmental amenities and disamenities: methods and applications. Annu. Rev. Environ. Resour. 34, 325–347.

Mishan, E.J., 1974. Economics of Disamenity. Nat. Resour. J. 14, 55.

Morgan, A., 2007. The impact of Hurricane Ivan on expected flood losses, perceived flood risk, and property values. J. Hous. Res. 16 (1), 47–60.

Mozumder, P., Helton, R., Berrens, R.P., 2009. Provision of a wildfire risk map: informing residents in the wildland urban interface. Risk Anal. 29 (11), 1588–1600.

Mueller, J.M., Loomis, J.B., 2008. Spatial dependence in hedonic property models: do different corrections for spatial dependence result in economically significant differences in estimated implicit prices? J. Agric. Resour. Econ. 212–231.

Mueller, J., Loomis, J., Gonzalez-Caban, A., 2009. Do repeated wildfires change Homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. J. Real Estate Financ. Econ. 38, 155–172.

Netusil, N.R., Chattopadhyay, S., Kovacs, K.F., 2010. Estimating the demand for tree canopy: a second-stage hedonic price analysis in Portland, Oregon. Land Econ. 86 (2), 281–293.

Nowak, D.J., Stein, S.M., Randler, P.B., Greenfield, E.J., Comas, S.J., Carr, M.A., Alig, R.J., 2010. Sustaining America's Urban Trees and Forests: A Forests on the Edge Report. Gen. Tech. Rep. NRS-62, U.S.Department of Agriculture, Forest Service, Northern Research Station

Palmquist, R.B., 1983. Estimating the demand for the characteristics of housing. Rev. Econ. Stat. 66 (394-404212-231).

Paveglio, T.B., Moseley, C., Carroll, M.S., Williams, D.R., Davis, E.J., Fischer, A.P., 2015. Categorizing the social context of the Wildland Urban Interface: adaptive capacity for wildfire and community “archetypes”. For. Sci. 61 (2), 298–310.

Radeloff, V.C., Hammer, R.B., Stewart, S.I., Fried, J.S., Holcomb, S.S., McKeefry, J.F., 2005. The wildland-urban interface in the United States. Ecol. Appl. 15 (3), 799–805.

Rasker, R., 2015. Resolving the increasing risk from wildfires in the American west. Solutions 6 (2), 48–55 (- http://www.thesolutionsjournal.com/node/237329).

Ridker, R., Henning, J.A., 1967. The determinants of residential property values with special reference to air pollution. Rev. Econ. Stat. 1 (49), 246–257.

Shafran, A.P., 2008. Risk externalities and the problem of wildfire risk. J. Urban Econ. 64 (2), 488–495.

Smith, V.K., Huang, J.C., 1993. Hedonic models and air pollution: twenty-five years and counting. Environ. Resour. Econ. 3, 381–394.

Stetler, K.M., Venn, T.J., Calkin, D.E., 2010. The effects of wildfire and environmental amenities on property values in Northwest Montana, USA. Ecol. Econ. 69 (11), 2233–2243.

Stewart, K.G., 2005. Introduction to Applied Econometrics. Thomson Brooks/Cole, Belmont, CA.

Talberth, J., Berrens, R.P., McKee, M., Jones, M., 2006. Averting and insurance decisions in the wildland–urban interface: implications of survey and experimental data for wildfire risk reduction policy. Contemp. Econ. Policy 24 (2), 203–223.

Taylor, L.O., 2003. The Hedonic Method. In: Champ, P., Brown, T., Boyle, K. (Eds.), A Primer on Nonmarket Valuation. Kluwer Academic Publishers, The Netherlands, pp. 331–393.

Theobald, D.M., Romme, W.H., 2007. Expansion of the US wildland-urban interface. Landsc. Urban Plan. 83 (4), 340–354.

Tobler, W.R., 1970. A computer movie simulating urban growth in the Detroit region. Econ. Geogr. 234–240.

USDA, USDI, 2001. Urban wildland interface communities within vicinity of federal lands that are at high risk from wildfire. Fed. Regist. 66, 751–777.

Venn, T.J., Calkin, D.E., 2011. Accommodating non-market values in evaluation of wildfire management in the United States: challenges and opportunities. Int. J. Wildland Fire 20 (3), 327–339.

Westerling, A.L., Hidalgo, H.G., Cayan, D.R., Swetnam, T.W., 2006. Warming and earlier spring increase western U.S. forest wildfire activity. Science 313, 940–943.

Yoder, J., Gebert, K., 2012. An econometric model for ex ante prediction wildfire suppression costs. J. For. Econ. 18, 76–89.