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RESEARCH ARTICLE

The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of California and Colorado

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Abstract
Context Wildfires destroy thousands of buildings every year in the wildland urban interface. However, fire typically only destroys a fraction of the buildings within a given fire perimeter, suggesting more could be done to mitigate risk if we understood how to configure residential landscapes so that both people and buildings could survive fire.
Objectives Our goal was to understand the relative importance of vegetation, topography and spatial arrangement of buildings on building loss, within the fire's landscape context.
Methods We analyzed two fires: one in San Diego, CA and another in Boulder, CO. We analyzed Google Earth historical imagery to digitize buildings exposed to the fires, a geographic information system to measure some of the explanatory variables, and FRAGSTATS to quantify landscape metrics. Using logistic regression we conducted an exhaustive model search to select the best models.
Results The type of variables that were important varied across communities. We found complex spatial effects and no single model explained building loss everywhere, but topography and the spatial arrangement of buildings explained most of the variability in building losses. Vegetation connectivity was more important than vegetation type.
Conclusions Location and spatial arrangement of buildings affect which buildings burn in a wildfire, which is important for urban planning, building siting, landscape design of future development, and to target

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fire prevention, fuel reduction, and homeowner education efforts in existing communities. Landscape context of buildings and communities is an important aspect of building loss, and if taken into consideration, could help communities adapt to fire.

Keywords WUI · Building loss · Wildfires · FRAGSTATS · Logistic regression · Best-subsets

Introduction

Wildfires are an integral part of many terrestrial ecosystems (Pausas and Keeley 2009), but in a changing climate, wildfires are becoming more frequent, extensive, and destructive (Pechony and Shindell 2010; Brotons et al. 2013). As houses are built in or near wildlands, and the wildland urban interface (WUI) continues to grow (Radeloff et al. 2005; Hammer et al. 2009b), future wildfires may cause catastrophic losses of property, and sometimes life (Karter 2010). However, when fire occurs, typically not all houses burn, raising the question, what determines which houses burn? In most cases, there will be multiple factors at play, ranging from building materials to the surroundings of a house. What is not clear though is the relative importance of factors such as vegetation, topography, and the spatial arrangement of buildings.

Several recent pieces of legislation, including the National Fire Plan and the Healthy Forest Restoration Act, were at least partly motivated by the goal to reduce fire risk in the WUI (Radeloff et al. 2005; Stewart et al. 2007, 2009; Hammer et al. 2009a). The need to reduce fire risk arises because the social, economic, and ecological losses from wildfire were and still are mounting, despite major fire prevention and suppression efforts (Syphard et al. 2008). This is why the protection of homes and lives is a main objective of wildland fire agencies across the United States, with widespread efforts to treat fuels, and some examples of programs to raise community awareness and preparedness. Landscape context and the location and spatial arrangement of buildings may be other important factors to consider though when aiming to reduce fire risk, especially when new housing developments are planned, and our study was designed to investigate how important these factors are.

Vegetation greatly affects wildfire behavior and is thus a main focus of wildfire prevention efforts (Andreu et al. 2013; Stevens et al. 2014; Kennedy and Johnson 2014). In addition to vegetation, topography influences the spatial variability of fuels and the biophysical conditions that determine fire spread, intensity and duration (Dillon et al. 2011). Topography influences fire behavior as well as vegetation distribution and productivity (Barbour et al. 1999), by affecting energy and water balances that control vegetation development, and hence the amount of biomass that can become fuel when sufficiently dry (Dillon et al. 2011). Elevation, aspect, latitude, and topographic position all influence microclimatic conditions, such as temperature, precipitation, direct solar radiation, wind exposure, etc., which in turn influence the moisture content of fuel (Dillon et al. 2011). Type, spatial pattern and distribution of vegetation determine the probability of fire ignition, fire spread rate and intensity, and ultimately, the type of vegetation that will regenerate after the fire (Marlon et al. 2012). Indirectly, topography can affect ignition probability because steep slopes, ridge tops, and south-facing slopes are all characterized by drier fuel conditions (Haire and McGarigal 2009). Weather conditions can strongly affect fire behavior. Humidity and temperature determine the rate at which fuels dry (Westerling et al. 2006; Finney et al. 2010), and wind also dries fuels, provides the fire with oxygen, and governs fire direction and spread rate (Bessie and Johnson 1995). However, neither fire spread data nor weather data was available at scales fine enough to determine the weather condition of a given building at the exact time it was hit by a fire, making it ill-suited to the scale of our analysis.

While vegetation, topography, and weather influence fire occurrence and behavior, these factors are not the only reason why some buildings burn within the perimeters of a fire and others do not. Factors related to the building themselves are also important, including building location and the spatial arrangement of buildings (Gibbons et al. 2012; Syphard et al. 2012). The probability that a building is lost is highest in small, isolated building clusters with low to intermediate building density and few roads (Bar-Massada et al. 2009; Syphard et al. 2012; Maranghides et al. 2013). What is unclear though is the relative importance of vegetation and building location to the probability that a building will be lost when a wildfire occurs, and how much this relative importance varies by setting.

There are several reasons why it is important to understand which buildings are likely to be lost if a fire occurs, and especially which roles the location and the spatial patterns of buildings play. Understanding where buildings are more likely to be lost is important when planning future development (Syphard et al. 2013). If there are ways to place new buildings so that the chances of loss to fire are reduced, then that could be one important step towards more fire-adapted communities. Knowing where buildings are most likely to burn is also important for established communities because this information can inform mitigation efforts. For example, a building in a higher-risk location may require a larger defensible space than one in a lower-risk area.

Ultimately, all mitigation strategies have strengths and weaknesses, and no single mitigation strategy will suffice to stem the rise in the number of buildings lost to wildfire. Vegetation management aimed at removing biomass to reduce fire intensity and risk (Agee and Skinner 2005) can be highly effective in the short run, but requires large and recurring investments of time and money. Furthermore, vegetation management can have negative ecological impacts, and may not be effective in some ecosystem types, or for fires that occur under severe weather conditions (Merriam et al. 2006; Syphard et al. 2011; Moritz et al. 2014). Nonetheless, the U.S. National Fire Plan (NFP), which aims to reduce the risks of catastrophic wildland fire to communities (USDA 2007), is focusing resources on fuel reduction efforts, especially in the WUI (Husari et al. 2006; Schoennagel et al. 2009).

In addition to fuel reduction efforts, mitigation actions available to homeowners and legislators (for new construction) include the use of fire resistant building materials to limit fire spread and building ignitions (Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gude et al. 2008). The combination of the buildings' exterior materials with its exposure to flames and firebrands ultimately determines its likelihood of ignition (Cohen 2000). Wildfire cannot ignite buildings unless their surroundings supply the necessary heat from flames of adjacent burning materials, such as firewood piles, flammable vegetation, neighboring buildings, or firebrands (Cohen 2000; Nowicki and Schulke 2002). Building materials are also important. As an extreme example, a concrete bunker would not ignite during a wildfire, while a building with a wooden roof could ignite without any flames in its vicinity due to firebrands (Cohen 2000; Quarles et al. 2010). In sum, a building's ignition potential during a wildfire is determined by the characteristics of its exterior materials, the characteristics of the surroundings within 30 m (i.e., the home ignition zone (Cohen 2008; Syphard et al. 2014), and the occurrence of fire brands, which can travel up to 2500 m (Cohen 2000). This means that a variety of actions to manage building materials and residential lots is necessary to reduce fire risk.

In addition, current wildfire policy recommendations are urging work at the level of homeowners and throughout a community to enact multiple mitigation strategies and create fire-adapted communities (e.g., Schwab and Meck 2005), and such efforts may hold promise over the long term. However, choosing among potential management actions, requires knowledge of which factors determine building loss and how their relative importance might vary with site characteristics.

Our goal was to understand the effects of vegetation, topography and spatial patterns of buildings on the probability of building loss when a wildfire occurs. Furthermore, we were interested to see how much the relative importance of these variables differs among landscapes and communities.

Methods

Study areas

We analyzed two fires from two ecoregions in the US where fires are frequent and building losses have been high in recent years: the Cedar fire, which occurred in San Diego County, California in October 2003, and the Fourmile Canyon fire, which occurred in Boulder County, Colorado in September 2010.

Most of California has a Mediterranean climate, and major metropolitan areas are juxtaposed with highly flammable ecosystems (Syphard et al. 2009). The dominant vegetation types are coastal sage scrub, chaparral, oak woodland and oak forest, and at higher elevations, pine forest (CDF 2003). The WUI fire problem is particularly critical in southern California, where the highest losses of property and life from wildfires in the US occur, and 400 buildings are lost every year on average (Calfire 2000; Alexandre et al.

2015). San Diego is a major, growing city in a particularly fire prone area. Its Mediterranean climate of cool, wet winters and long, dry summers creates dry fuels, and the autumnal, adiabatic Santa Ana wind can result in severe fire weather. The Cedar fire started near San Diego in the afternoon of October 25th 2003 when a lost hunter set a fire to signal for help (CDF 2003). It burned for 10 days, during which time it covered 110,579 ha, claimed the lives of 13 civilians and one firefighter, injured 91 people, and destroyed more than 2500 buildings (Fig. 1).

Fire regimes in Colorado are influenced by the El Niño-Southern Oscillation (ENSO), which drive year-to-year variability in moisture, with dry conditions linked to reduced amplitude of the ENSO (Kitzberger et al. 2001). In addition, the negative, cool phase of the Pacific Decadal Oscillation (PDO) is sometimes associated with increased drought in the southern Rockies when coupled with the positive (warm) phase of the Atlantic Multidecadal Oscillation (MDO) (Sibold and Veblen 2006). These broad-scale climate patterns can cause severe droughts resulting in conditions in which

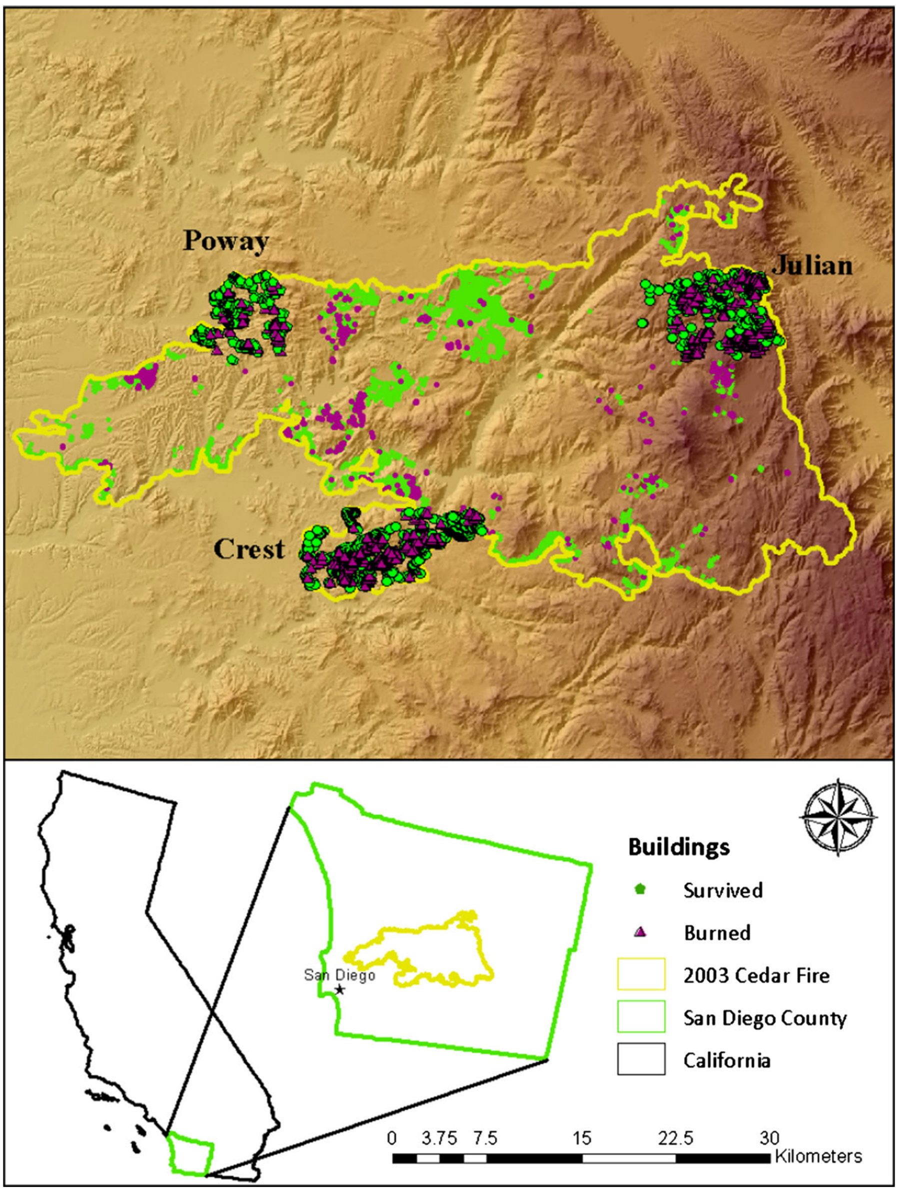

Fig. 1 Cedar Fire perimeter with the three communities, Crest, Julian and Poway, and their affected buildings in San Diego, California, 2003

large fires can occur (Sibold and Veblen 2006). Dominant vegetation types are ponderosa Pine (*Pinus ponderosa*), ponderosa pine/juniper (Juniperus spp.), and Douglas-fir (*Pseudotsugamenziesii*)/ponderosa pine forests (Graham et al. 2012). Between 2006 and 2011, Colorado lost 476 buildings to wildfire (Graham et al. 2012). Boulder, Colorado, is a medium sized city located in the Northern Colorado Front Range, where the Rocky Mountains meet the Great Plains. The Fourmile fire started on the morning of September 6th 2010 in the Rocky Mountain Front Range adjacent to Boulder under dry conditions and steady winds. It was active for 11 days, during which time it covered 2307 ha and destroyed 331 buildings, a statewide record number at that time (Fig. 2).

Data

The probability of building loss due to wildfire is potentially affected by several predictor variables operating at different spatial scales. We measured all variables at one of three spatial scales:

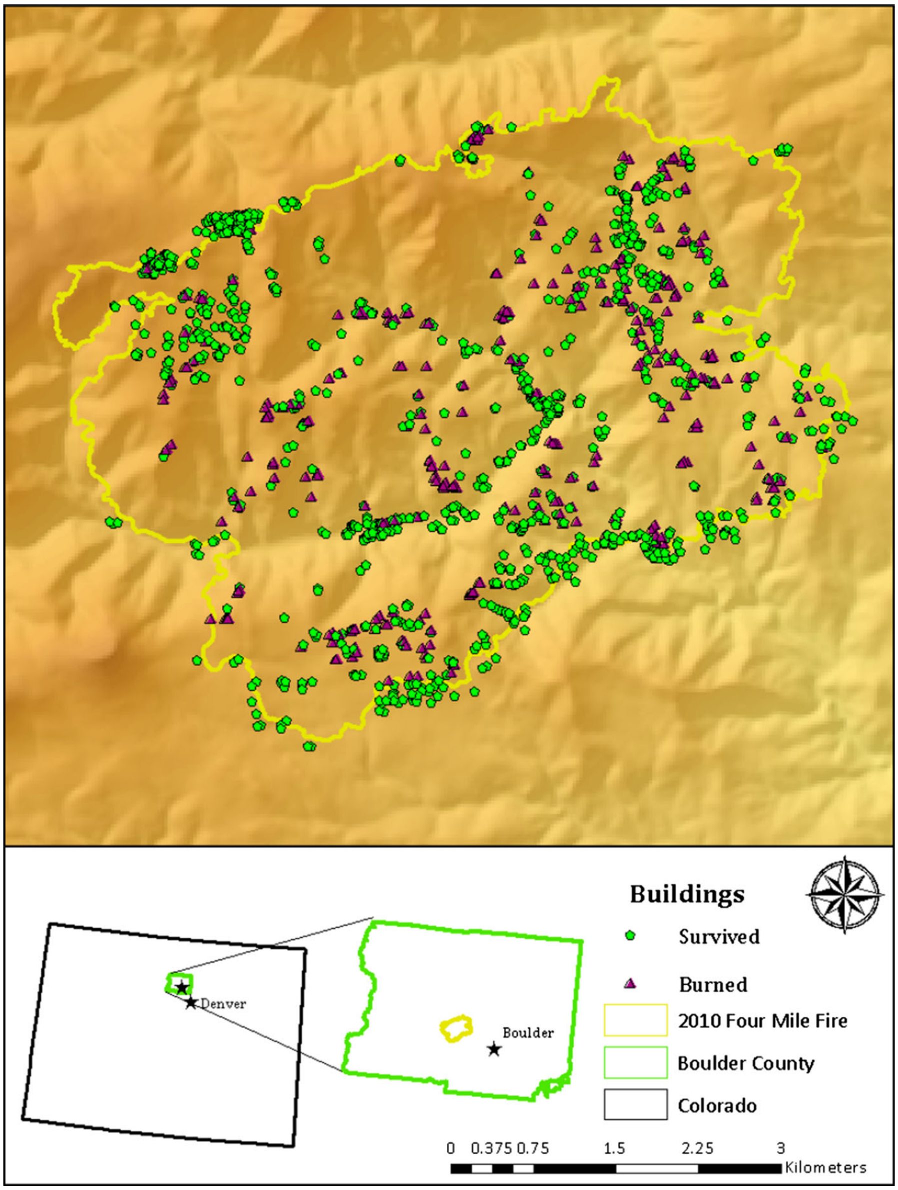

Fig. 2 Fourmile Fire perimeter and affected buildings in Boulder, Colorado, 2010

(1) The building scale, where we derived variables at the location of a building, or averaged within 30 m of each building (30 m is the distance from a heat source beyond which a building is not likely to ignite;(Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gibbons et al. 2012);
(2) The neighborhood scale, where we considered buildings within 200 m of each other as part of the same neighborhood (Syphard et al. 2007a); and
(3) The landscape scale, defined as the area within 2500 m of each building, where we calculated landscape metrics. The 2500 m distance is the approximate distance up to which wind might carry an ember or fire brand during a fire event (Cohen 2000). The exact distance will depend on wind conditions at the day of the fire.

Building data

We used Google Earth's historical imagery to collect spatially explicit data on building loss due to wildfires (Fig. 3), where we distinguished buildings that were destroyed from those that did not burn. For the Cedar fire, we digitized all the buildings within the fire perimeter (USDA 2011) from Google Earth imagery before and after the wildfires. We digitized a total of 15,543 buildings, of which 1715 were destroyed. We considered a building to be destroyed when it burned to the ground and was no longer standing. We were not able to assess buildings that were damaged by the fire, for example by smoke damage or partial siding melt. We considered all buildings that were still standing after the fire as "surviving buildings."

All the buildings inside the Fourmile fire were digitized by Boulder County and are available online (Boulder County Colorado 2015). A total of 1122 buildings were digitized, and 174 residential buildings plus 157 accessory buildings were destroyed by the fire.

Vegetation data

We analyzed land cover data from the National Land Cover Dataset (NLCD2006, 30-m spatial resolution, Fry et al. 2011) and reclassified the land cover types as highly flammable, flammable, or non-flammable (Online Appendix 1). Vegetation alone does not constitute a fuel model and information on different vegetation types does not provide the same amount of information with regards to fire behavior as fuel models do. Fire behavior generally varies according to vegetation type and we used vegetation as a proxy for potential fuels. The two most extensive NLCD classes inside both fire perimeters were Evergreen forests (42), and Shrub/Scrub (52). Evergreen forests and shrubs differ in terms of fire behavior, but both can support intense fires that can produce firebrands and ignitions far ahead of the fire front. Grassland areas tend to be highly flammable, especially in the dry season, and as such may exhibit fires that lead to home ignition

Fig. 3 Example of Google Earth imagery before and after the Fourmile Fire in Colorado in 2010

(Knapp 1998; Mell et al. 2007). We therefore classified Evergreen Forest, Mixed forest, Shrub/Scrub, and Grassland/Herbaceous classes as highly flammable. Deciduous Forest, Pasture/Hay, and Crops are vegetation classes that can support fire spread in some seasons, but because hay and crop harvest occurs typically before moisture levels drop, and therefore are less likely to produce a fire that will ignite a building, we classified them as flammable. We classified the remaining NLCD classes as not flammable due to their lack of vegetation or because their moisture content is too high to sustain a fire.

At the landscape level, we calculated landscape metrics based on the reclassified NLCD and the program Fragstats (McGarigal et al. 2012). The landscape metrics provided a measure of fuel configuration and connectivity in the area surrounding each building, which are important factors for fire occurrence and spread in the vicinity of buildings. We calculated two landscape metrics within 2500 m from each building: the Contagion Index (CONTAG) and Connectance Index (CONNECT). In addition, we calculated the percentage of Land ($PLAND_i$) that each class occupied and the total number of patches for each class (NP_i—see Online Appendix 2 for definitions).

In addition to the NLCD, we collected the Existing Vegetation Type (EVT), and Fuel Characteristic Classification System Fuelbeds (FCCS), at the building level, from LANDFIRE version 1.0.5 (http://www.landfire.gov) as proxies for the flammable vegetation and fuels aroundeachbuilding.EVT represents vegetation conditions around the year 2001, i.e., before either fire occurred. EVT values are calculated using several sources of information, including field data, elevation, Landsat imagery, NLCD, and biophysical gradient data, and are widely used as proxies for fuel in several other LANDFIRE fuel models and fire behavior models (http://www.landfire.gov). FCCS define a fuelbed as the inherent physical characteristics of fuel that contribute to fire behavior (Riccardi et al. 2007). Fuelbeds represent a wide range of fuel characteristics in six horizontal fuel layers called strata (Ottmar et al. 2007). Strata include canopy, shrub, non-woody vegetation, woody fuel, litter/lichen/moss, and ground fuel. Each stratum is further divided into 16 categories and 20 subcategories to represent the complexity of wildland and managed fuel (http://www.landfire.gov). We were interested in knowing which of these vegetation-related variables were most strongly related to building loss, and thus most useful for future modeling of building loss to fire.

Topographic data

Topographic variables that affect fire behavior include elevation and aspect, which affect moisture gradients, and topographic features like narrow valleys or steep slopes, which influence fire spread. Topography also affects vegetation distribution and productivity (Barbour et al. 1999) because it affects energy and water balances (Dillon et al. 2011), and therefore precipitation, runoff, temperature, wind and solar radiation (Daly et al. 1994).

We included several topographic variables, including elevation, slope, topographic position index (TPI), and southwestness derived from aspect (Syphard et al. 2007b). Slope and elevation were acquired from LANDFIRE and are derived from the National Elevation Dataset (NED, ned.usgs.gov, verified on 01/06/2015). LANDFIRE elevation data has a 30-m resolution and covers the entire United States (U. S. Geological Survey 2013) We also used the Digital Elevation Model (DEM) from LANDFIRE to calculate the topographic position index (TPI) using an algorithm that defines standardized threshold values for the difference between a cell elevation value and the average elevation of the cells around that cell measured in standard deviations from the mean (Jenness 2006). Topographic position is a categorical variable that refers to landscape position (i.e., valley, lower slope, gentle slope, steep slope, upper slope, ridges). The algorithm results in a categorical raster that contains values between 1 and 6 to represent the topographic position:

1. Valley: TPI ≤ -1 SD
2. Lower Slope: -1 SD $<$ TPI ≤ -0.5 SD
3. Flat Slope: -0.5 SD $<$ TPI $<$ 0.5 SD, Slope $\leq 5°$
4. Middle Slope: -0.5 SD $<$ TPI $<$ 0.5 SD, Slope $> 5°$
5. Upper Slope: 0.5 SD $<$ TPI $\leq$ 1 SD
6. Ridge: TPI $>$ 1 SD

While weather also affects fire behavior, we were not able to include weather data in our analysis because, neither fire spread data nor weather data was available at scales fine enough to determine the weather conditions of a given building at the exact

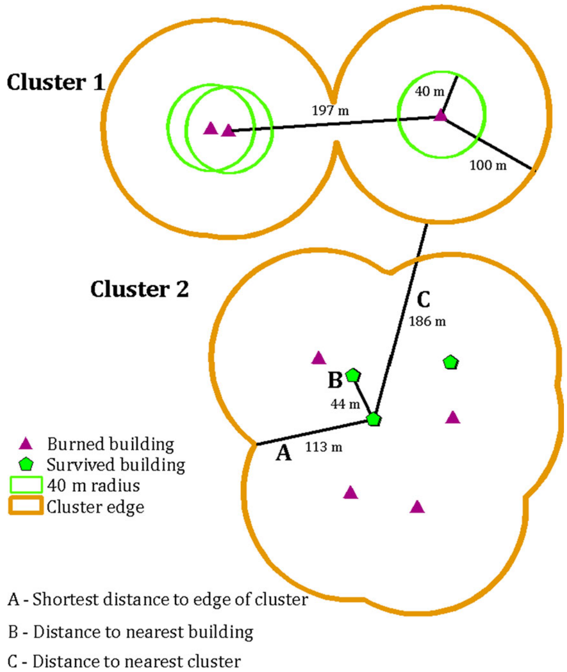

Fig. 4 Example of clusters that were created using a radius of 100 m; Cluster 1: example of how the buildings within 40 m were calculated. The two buildings on the left would have one building within 40 m each, while the building on the right would have zero buildings. Cluster 2: examples of how distance to the edge of cluster, distance to the nearest building and distance to the nearest cluster were calculated

time it was hit by a fire, making it ill-suited to the scale of our analysis.

Spatial arrangement of buildings

To quantify the spatial pattern of buildings, we analyzed spatial relationships among individual buildings and the arrangement of buildings within clusters. Clusters were created by placing a circular radius of 100 m around each building. Overlapping circles were merged to become part of the same cluster. Clusters defined the Neighborhood level of our analyses (Fig. 4). For each cluster we calculated total area, total number of buildings, building dispersion (Eq. 1), and building density (Eq. 2).

$$\textit{Building dispersion} = \frac{\textit{st dev of the dist. among buildings within a cluster}}{\textit{mean dist. among buildings within a cluster}} \tag{1}$$

$$\textit{Building density} = \frac{\textit{number of buildings within a cluster}}{\textit{cluster area (ha)}} \tag{2}$$

We also calculated the distance to the edge of the nearest neighboring cluster and the closest building, and the distance from each individual building to the edge of the cluster (Fig. 4), based on research indicating that buildings in the interior of a cluster are less susceptible to wildfire than those at its edge (Syphard et al. 2012; Maranghides et al. 2013). At the Building level we counted the number of buildings within 40 m of each building (Fig. 4). For a complete list of all the variables used in the models, see Table 1.

Statistical analyses

We analyzed all data with the statistical software R (R Core Team 2014). We performed exploratory analysis of the data by plotting scatterplots and calculating summaries. Our response variable was whether a building was destroyed by fire or survived, and hence a binary variable. Thus, we selected logistic regression to model the relationships between the probability of building loss as a function of our predictor variables (Hosmer and Lemeshow 2000).

In our preliminary statistical analyses, we parameterized a model for the entire Cedar fire perimeter, based on all the buildings within the perimeter (total of 13,543 buildings). However, the semivariograms showed spatial patterns indicating the need to parameterize models for sub-regions the Cedar fire. Similarly, when we mapped the residuals, there was strong evidence of spatial clustering. We therefore split the California study area into three separate communities within the perimeter of the Cedar fire: Crest, Julian, and Poway; and analyzed them separately (Fig. 1). This left us with three separate models for which the autocorrelation conformed to a more typical and more easily modeled form that could be adequately handled with a generalized linear mixed models (GLMMs), using penalized quasi likelihood (PQL), and one model for the Fourmile fire as a whole.

We conducted model selection based on an exhaustive search of all possible combinations of predictor variables, selecting up to seven of them per model, and selected the best models based on the Bayesian

Table 1 Variables used in the models, their meaning and sources

Response variable: destroyed (1) versus survived (0)

Level of analysis	Variable	Description	Source
Building level (40 m radius)	Vegetation type[B]	Existing Vegetation Type, represents the species composition currently present at a given site	LANDFIRE EVT (http://www.landfire.gov/NationalProductDescriptions21.php)
	Fuel characteristic classification system fuelbeds[B]	The fuel characteristic classification system fuelbeds (FCCS) layer describes the physical characteristics of a relatively uniform unit on a landscape that represents a distinct fire environment. FCCS provides standardized descriptions of fuelbeds and fire hazard	LANDFIRE FCCS (http://www.landfire.gov/NationalProductDescriptions25.php)
	Land cover class[B]	See Online Appendix 1 for details on cover classes	NLCD 2006 or 2001
	Elevation[B]	Digital elevation model, 30 meters resolution	LANDFIRE DEM (http://www.landfire.gov/NationalProductDescriptions7.php)
	Slope[B]	Slope calculated in degrees	Derived from DEM
	Topographic position[B]	6 Classes, extansion tool on ArcMap	Jenness 2006
	Southwestness[B]	Create a new field and calculate the cosin(ASP) in ArcMap	Calculated by us
	Buildings within 40 m radius[B]	Derived from digitized buildings	Calculated by us
Cluster level (cluster—groups of buildings that are within 100 m)	Building density[C]	Number of buildings within a cluster divided by the cluster area	Calculated by us
	Cluster size[C]	Cluster area (m2)	Calculated by us
	Building dispersion[C]	Standard deviation of the distance among buildings within a cluster divided by the mean distance among buildings within the cluster	Calculated by us
	Number of buildings inside cluster[C]	Derived from digitized buildings	Calculated by us
	Distance to edge of cluster[C]	Derived from digitized buildings	Calculated by us
	Distance to nearest building[C]	Derived from digitized buildings	Calculated by us
	Distance to nearest cluster[C]	Derived from digitized buildings	Calculated by us
Landscape level (radius of 2500 m)	Percentage of land/class[L]	See Online Appendix 2 for detailed description	FRAGSTATS
	Number of patches/class[L]		FRAGSTATS
	Contagion Index[L]		FRAGSTATS
	Connectance Index[L]		FRAGSTATS

Superscripts *B* building, *C* cluster and *L* landscape are used with variable names throughout tables and text to denote the level of measurement

Information Criterion (BIC) (Schwarz 1978), and the single best for each community. We conducted the search with the R packages *bestglm* (McLeod and Xu 2011) when possible, and *glmulti* (Calcagno 2013) when the number of explanatory variables was larger than 32. In this first set of variables, we did not account for spatial autocorrelation, and therefore we refer to these models as the 'non-spatial models.'

We checked for spatial autocorrelation in the residuals by plotting semivariograms (R package *geoR*, Ribeiro and Diggle 2001) for the top model in each community (see supplementary material). Because we found evidence of spatial autocorrelation in the residuals of the models for all four communities, we used generalized linear mixed models (GLMMs), using penalized quasi likelihood (PQL), to account for spatial autocorrelation (R package *nlme*; (Pinheiro et al. 2014). Hereafter we shall refer to these as the 'spatial models.' Since the BIC cannot be used to assess the fit of a GLMM based on PQL, (PQL is not a true likelihood), we incorporated spatial autocorrelation only into the top non-spatial model for each community and applied backward selection to remove extraneous variables (p-values higher than 0.05 were excluded).

To measure the discriminatory ability of both the spatial and non-spatial models, we calculated the area under the curve (AUC) of the receiver operating characteristic (ROC) curve (R package *ROCR*, (Sander and Lengauer 2005). In the case of the spatial models, we calculated the AUC based on the fixed effects coefficients, since there is no straightforward way to calculate the AUC for models with random effects. This means that the AUC values for the spatial models are only an approximation.

Results

Our initial list of variables included 23 potential explanatory variables and we were able to reduce it to eight variables for all four communities. Our goal was to understand the effect of vegetation, topography and spatial arrangement of buildings on the probability of building loss to wildfire. Hence we looked at each type of variable and their relative impact on building loss.

Given that our models are the results of an exhaustive model search methodology using logistic regression with spatial components, there is no meaningful way to define variance explained by each variable. However, in such a search the top model is generally a good representation of the variables' importance, and in our case identifies which variables are most relevant in explaining building loss.

Vegetation variables

We included seven variables related to vegetation in our analysis: vegetation type^{B}, land cover class^{B}, fuel characteristic classification system fuelbeds^{B}, percentage of highly flammable vegetation within 2500 m^{L}, number of patches for each class within 2500 m^{L}, contagion index of the landscape within 2500 m^{L}, and connectivity of the landscape within 2500 m^{L}. Vegetation-related variables were part of the best non-spatial and spatial models for three of the four communities.

Percentage of highly flammable land^{L} was present in both spatial and non-spatial models in Boulder, and in the non-spatial model of the Crest community (Table 2). In both Boulder and Crest communities, the probability of building loss given a wildfire increased with higher percentages of highly flammable land surrounding the buildings.

Contagion^{L} was present in the non-spatial model for Boulder, but not in the spatial model and it had negative signal, meaning that lower contagion values for the landscape around the building represent higher risk of building loss (Table 2).

Connectivity^{L} was present in both the best spatial and the best non-spatial models of the Julian community, with higher connectivity values representing higher risk of building loss (Table 2).

Number of patches of highly flammable land^{L} was in both the spatial and non-spatial models of the Poway community, with a smaller number of patches of highly flammable land representing higher risk for building loss (Table 2).

It is noteworthy that all the vegetation-related variables that were included in our best spatial models were landscape-level variables (Table 3).

Topography variables

We included four variables related to topography in our analysis: elevation^{B}, slope^{B}, topographic position^{B} and southwestness^{B}. Elevation^{B}, topographic position index^{B}, and slope^{B} were part of the best non-spatial models for three of four communities (Table 2). In the Cedar fire, elevation^{B} was important in non-spatial models of two of the three communities (Tables 2 and 3). In the Crest community, the probability of building loss was higher for buildings located at higher elevations^{B} and on steeper slopes^{B}.

Table 2 Coefficients, standard errors, and p-values for the top model, with (glmmPQL) and without (glm) spatial components, for all communities

	GLM					glmmPQL			
	Coefficient	SE	p value	BIC*	AUC	Coefficient	SE	p value	AUC
Boulder, CO									
Intercept	−249.30	33.14	$p < 0.001$	1279	0.69	−119.61	27.75	$p < 0.001$	0.66
Elevation^B	0.01	0.00	$p < 0.001$			0.01	0.00	$p < 0.001$	
Distance to edge cluster^C	−0.02	0.01	0.002			–	–	–	
Contagion Index^L	−0.54	0.12	$p < 0.001$			–	–	–	
Percentage of highly flammable land	2.92	0.43	$p < 0.001$			1.09	0.26	$p < 0.001$	
Crest, San Diego, CA									
Intercept	−834.70	143.00	$p < 0.001$	1075	0.79	−10.08	2.05	0.00	0.73
Elevation^B	0.01	0.00	$p < 0.001$			0.01	0.00	0.00	
Slope^B	0.11	0.02	$p < 0.001$			0.07	0.02	0.00	
TPI—top RIDGES^B	−0.68	0.17	$p < 0.001$			–	–	–	
Buildings within 40 m^B	−0.39	0.11	$p < 0.001$			–	–	–	
Building density^C	−1.10	0.32	$p < 0.001$			–	–	–	
Percentage of highly flammable land^L	8.16	1.42	$p < 0.001$			–	–	–	
Percentage of non-flammable land^L	8.44	1.47	$p < 0.001$			–	–	–	
Julian, San Diego, CA									
Intercept	−1.34	0.35	0.043	2623	0.75	−2.64	0.43	$p < 0.001$	0.72
Elevation^B	0.00	0.00	$p < 0.001$			–	–	–	
Buildings within 40 m^B	0.17	0.03	$p < 0.001$			–	–	–	
Cluster size^C	−0.01	0.00	$p < 0.001$			−0.01	0.00	0.038	
Number of buildings in the cluster^C	0.01	0.00	$p < 0.001$			0.00	0.00	0.033	
Distance to nearest cluster^C	0.00	0.00	0.009			–	–	–	
Connectance index^L	0.31	0.04	$p < 0.001$			0.25	0.06	$p < 0.001$	
Poway, San Diego, CA									
Intercept	−0.81	0.27	0.003	294	0.78	−0.81	0.26	0.002	0.78
Building density^C	−0.82	0.24	$p < 0.001$			−0.82	0.23	$p < 0.001$	
Number of patches of highly flammable land^L	−0.04	0.01	$p < 0.001$			−0.04	0.01	$p < 0.001$	

* BIC values showed here are the absolute values and were used solely to rank the models and not for comparisons among models

Spatial-arrangement of buildings

Spatial-arrangement variables were included in the final spatial models of two of the four communities analyzed (Table 3). We included in our analysis eight variables related to spatial arrangement of buildings, and six of those variables were present in the non-spatial models for all communities. Three out of the eight variables were present in the spatial models for two communities: number of buildings in the cluster^C, building density^C, and cluster size^C. However, the results varied from one community to another, and what was selected in the model for one community was typically not included in models for the other. These results highlighted the importance of spatial arrangement since it was the most prevalent group of variables in both spatial and non-spatial models. In the Julian community, the probability of building loss given a wildfire was greater when the cluster size^C was smaller and when there was a larger number of buildings within a cluster. In the Poway community, however, the probability of building loss was greater when building density^C was lower.

Table 3 Variables present in the top models that account for spatial autocorrelation for each community

Communitiy	Vegetation	Topography	Spatial arrangement	AUC for glm	AUC for glmmPQL*
Boulder	Percentage of highly flammable land[L]	Elevation[B]		0.69	0.66
Crest		Elevation[B] Slope[B]		0.79	0.73
Julian	Connectanceindex[L]		Cluster size[C] number of buildings in the cluster[C]	0.75	0.72
Poway	Number of patches of highly flammable land[L]		Building density[C]	0.78	0.78

* AUC for spatial models does not explicitly account for spatial autocorrelation

Discussion

When modeling which buildings burned within a fire perimeter, we found that variables describing the landscape—vegetation connectivity, topography, and the spatial arrangement of buildings—were present more frequently in the models than were the variables measuring more common targets of fire risk mitigation, such as vegetation type and vegetation cover.

We based our choice of variables in part on the work of Cohen and others whose investigation of building ignition and building loss to wildfires (Cohen and Butler 1998; Cohen 2000; Nowicki and Schulke 2002; Gibbons et al. 2012; Syphard et al. 2012) has strongly influenced recommendations made to homeowners and fire managers regarding structure protection and risk mitigation. We included variables similar to those previously found to be important in building ignition, though we measure these variables and assess relationships among them at the landscape scale, to clarify which contribute the most to the risk of building loss across a residential landscape.

Vegetation

Vegetation was present in models for three communities. Interestingly, it was not the type of vegetation that was present, but rather the amount and the connectivity of this vegetation that mattered most. These results may be due to the fact that the vegetation type was fairly uniform, in particular in the Fourmile fire where the vegetation cover was either Evergreen forest or shrub/scrub. The degree to which communities were different in terms of the factors determining building loss further underlines the importance of landscape factors in the risk of building loss.

The vegetation-related measures that we included (e.g., land cover, fuel beds, and vegetation type), and their consistent relatively lower importance demonstrated that once a fire starts and there is adequate vegetation to carry the fire, other factors become more important determinants of building loss. Vegetation and fuel is related to fire probability and fire spread and therefore fire exposure (Whitlock et al. 2003; Marlon et al. 2006), but less to building loss. The presence of vegetation near the building was not a strong predictor in our models of the likelihood that a building would be lost to the fire.

Topography

Across all locations and models, topographic characteristics such as elevation and slope, were selected in the model fitting. Topography can affect the outcome of a wildfire directly or indirectly. Directly, because topography influences fire spread and behavior. Steeper slopes decrease the angle between the flame and the new fuel source, drying fuels faster and therefore, moving up the hill faster (Dupuy 1995), and indirectly because buildings located at higher places are typically harder to access and therefore to defend (e.g. The Valparaiso fire in Chile, Associated Press 2014). The combination of faster moving flames with difficult access often results in building loss and was likely the reason why elevation was an important variable in the Fourmile fire.

Spatial arrangement of buildings

Spatial arrangement of buildings, including cluster size, number of buildings in the cluster, and building density, was also consistently important in our models.

For example, clusters with many buildings were associated with greater probability of loss in the case of the Julian community. This may be because burning buildings are themselves a source of firebrands that can be carried by the wind and ignite other buildings (Suzuki et al. 2014). Smaller clusters with more buildings will be denser, again increasing the probability of building-to-building ignition. However, the model for the Poway community showed higher risk in lower-density neighborhoods, perhaps reflecting an unmeasured covariate such as differences in the ease of accessibility for suppression or in the age and building materials of different neighborhoods. Fire-specific factors such as the time of day or sequence of the flame front's passage through the community could also be important and we were not able to consider them here (Maranghides et al. 2013).

Caveats

The relatively low AUC values suggest that factors not included in our models may also affect building loss. For example, construction materials (Cohen and Butler 1998; Cohen 2000), fire suppression efforts during the fire (Graham et al. 2012), weather conditions during the fire event, and vegetation in the home ignition zone (Cohen and Butler 1998; Nowicki and Schulke 2002; Cohen 2008) play a role in the outcome of wildfire events, including building loss. Due to the scale of our analysis and reliance on satellite imagery and remote sensing information to collect our data, it was not possible to include these factors in the models. We do acknowledge that wind influences how far a firebrand can reach, which may be why buildings closer to the edge are at greater risk under severe weather conditions. However, we did not account for weather because there was not enough variability in available weather data, particularly for the Cedar fire, which occurred under Santa Ana conditions. Furthermore, while including weather would be interesting from a scientific perspective, it is less relevant for community planning purposes, because weather conditions during future fires are not known.

The most important variables in the Fourmile fire were more closely related to topography and flammability of the landscape surrounding the buildings, than in the communities in San Diego. The AUC values were the lowest of all four communities and we can only speculate that we missed some variables, such as building materials, suppression efforts and pre-fire mitigation efforts on the property by the owners.

Despite the fact that many other variables could have been added to our initial list, we began with a broad set of 24 variables and reduced it to a fairly small, focused, collection of explanatory variables that resulted in good AUC values. We see this as a modeling success. The statistical methods used in this study are cutting-edge when dealing with binary dependent variables and spatial autocorrelation. As in any modeling approach, there is always a possibility for Type II errors and for that reason we used AUC to assess the quality of the models by looking at both matches and mismatches in the model estimates.

We would like to emphasize that our goal was to understand the underlying drivers to building loss and that we had no data that allowed us to cross-validate the models in a different place. Therefore, we did not try to use the models to make prediction for areas outside our study area. We did try each model on all other three communities and the results were always a model with a poor performance, strengthening our finding that the drivers are location specific and may not apply in other WUI areas.

Management implications

The defense of buildings and the replacement of destroyed buildings constitute a substantial portion of the costs associated with wildland fires in the WUI (Gude et al. 2013). Knowing *where on the landscape* buildings face the most risk could focus both mitigation and suppression efforts and inform land use planning, urban planning, and WUI regulation. This knowledge could also be used to expand and improve the fire risk information available to homeowners, and to highlight more location-specific factors (i.e., lot-related risk in addition to building material- and landscaping-related risk). Our findings have implications for policy makers, urban planners and homeowners, reinforcing the growing awareness that landscape configuration, as modified through land use and urban planning, and WUI building regulations, is a crucial focus for creating fire-adapted communities.

Past land-use decisions have placed many buildings in highly flammable areas resulting in high exposure and therefore, vulnerability to wildfires, of both buildings and people (Pincetl et al. 2008). Our results support other studies (Gibbons et al. 2012; Syphard et al. 2012) in highlighting that the location of a building on the landscape and in relation to other buildings matters greatly in terms of the probability that a building will burn when a fire occurs. This suggests that building placement could be given more weight when deciding which homeowners to focus on first in community outreach programs. WUI fire managers could prioritize reaching the owners of the highest-risk building locations, i.e., those at higher elevation, at the top of a ridge, in dense clusters of buildings, or at the periphery of a neighborhood, to make them aware that their building has a higher probability of loss than their neighborhood as a whole if a wildfire occurs, so that they can decide upon mitigation steps. While targeting higher-risk areas is currently a standard practice for community mitigation programs, such as Firewise, our study reinforces the significance of building placement *within high-risk areas,* and suggests it is a major risk factor.

While it is rarely feasible to alter existing development patterns, it may be possible to reduce future fire risk by more carefully siting new development in high fire-risk landscapes, or steering development away from such areas entirely, as is commonly done by U.S. communities to reduce vulnerability to other natural hazards such as flooding and landslides. In addition, rebuilding after a wildfire can be an opportunity to implement new mitigation actions, incentives and regulations such as those recommended under the 2012 International Code Council's Wildland Urban Interface Code, which has been added to the zoning codes of communities across the U.S. (available at ftp://law.resource.org/pub/us/code/ibr/icc.iwuic.2012.html Accessed July 7, 2015) (Alexandre et al. 2015; Mockrin et al. 2015). In this regard, our findings are especially important for community planning and zoning officials who want to reduce their community's vulnerability to fire. Similarly, land-use regulations intended to minimize fire risk must address landscape-level factors, including building location and arrangement (Syphard et al. 2012), if they are to be successful in reducing wildfire-related losses. Subdivision and planned unit development requirements are among the local regulations that directly govern the configuration of newly-built landscapes, suggesting these and other community-specific rules could be targeted for change. Vegetation connectivity is the province of landscape architects as well as landscape maintenance services, two additional groups whose cooperation in fire adaptation would be beneficial. Our study suggests that there are opportunities to be proactive about future risk by considering building locations and vegetation connectivity when planning new housing developments.

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