

Factors related to building loss due to wildfires in the conterminous United States

PATRICIA M. ALEXANDRE,^{1,6} SUSAN I. STEWART,¹ NICHOLAS S. KEULER,² MURRAY K. CLAYTON,²
MIRANDA H. MOCKRIN,³ AVI BAR-MASSADA,⁴ ALEXANDRA D. SYPHARD,⁵ AND VOLKER C. RADELOFF¹

¹*SILVIS Lab, Department of Forest and Wildlife Ecology, University of Wisconsin–Madison, 1630 Linden Drive, Madison, Wisconsin 53706 USA*

²*Department of Statistics, University of Wisconsin–Madison, 1300 University Avenue, Madison, Wisconsin 53706 USA*

³*Rocky Mountain Research Station, USDA Forest Service, 2253 Research Park Boulevard, Suite 350, Baltimore, Maryland 21228 USA*

⁴*Department of Biology and Environment, University of Haifa, Haifa, Israel*

⁵*Conservation Biology Institute, 10423 Sierra Vista Avenue, La Mesa, California 91941 USA*

Abstract. Wildfire is globally an important ecological disturbance affecting biochemical cycles and vegetation composition, but also puts people and their homes at risk. Suppressing wildfires has detrimental ecological effects and can promote larger and more intense wildfires when fuels accumulate, which increases the threat to buildings in the wildland–urban interface (WUI). Yet, when wildfires occur, typically only a small proportion of the buildings within the fire perimeter are lost, and the question is what determines which buildings burn. Our goal was to examine which factors are related to building loss when a wildfire occurs throughout the United States. We were particularly interested in the relative roles of vegetation, topography, and the spatial arrangement of buildings, and how their respective roles vary among ecoregions. We analyzed all fires that occurred within the conterminous United States from 2000 to 2010 and digitized which buildings were lost and which survived according to Google Earth historical imagery. We modeled the occurrence as well as the percentage of buildings lost within clusters using logistic and linear regression. Overall, variables related to topography and the spatial arrangement of buildings were more frequently present in the best 20 regression models than vegetation-related variables. In other words, specific locations in the landscape have a higher fire risk, and certain development patterns can exacerbate that risk. Fire policies and prevention efforts focused on vegetation management are important, but insufficient to solve current wildfire problems. Furthermore, the factors associated with building loss varied considerably among ecoregions suggesting that fire policy applied uniformly across the United States will not work equally well in all regions and that efforts to adapt communities to wildfires must be regionally tailored.

Key words: building loss; ecoregions; linear and logistic regression; national analysis; wildfires; wildland–urban interface.

INTRODUCTION

Severe wildfire is a growing threat to buildings in the wildland–urban interface (WUI), the area where houses meet or intermingle with undeveloped wildland vegetation (Radeloff et al. 2005). The number of buildings lost and the resources spent fighting fires (approximately two billion dollars per year for fuel management and suppression; Colburn 2008, USDA F. S. 2014) demonstrate how serious the wildland fire problem has become in the United States. Interestingly, though, when wildfires occur, typically only a small proportion of the buildings within the fire perimeter are lost (Alexandre et al. 2015), and one major gap in our knowledge of WUI fire is why

some buildings burn and others do not. Building materials and vegetation characteristics are important (Cohen 2000, Cary et al. 2009, Quarles et al. 2010, Maranghides and Mell 2012). However, building materials and vegetative fuel alone do not explain why only some buildings are destroyed (Alexandre et al. 2016). A few local studies conducted in California (USA), Colorado (USA), and Victoria (southeastern Australia), suggest that topography and the spatial arrangement of buildings are also key factors in building loss (Gibbons et al. 2012, Syphard et al. 2012, Alexandre et al. 2016), but it is unclear if these findings apply in other ecoregions. Successful fire policy and mitigation must be based on understanding how human and ecological factors interactively determine which buildings burn when a fire occurs, and how their relative importance changes among ecoregions.

Globally, wildfire is an important ecological disturbance that affects biochemical cycles and vegetation

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⁶E-mail: patmalico@fulbrightmail.org

composition (Thonicke et al. 2001) and maintains biodiversity in many areas (Pausas and Keeley 2009). Suppressing wildfires can have detrimental ecological effects in some dry forest types (Keeley et al. 1999), potentially promoting larger and more intense wildfires due to excess fuel accumulation and continuity (Covington and Moore 1994, Hessburg et al. 2007). However, too-frequent fire due to human-caused ignitions and invasive species can also threaten ecological functioning and biodiversity, especially in non-forested ecosystems (Brooks and Matchett 2006, Syphard et al. 2009). Deleterious ecological effects of changes in fire regimes are likely when broadscale fire management strategies do not account for the inherent variation in natural fire regimes (Moritz et al. 2014).

National fire policy in the United States, which originated after several years of severe fires between 1910 and 1935, (e.g., the Great Fire in 1910 in Idaho, Montana, and Washington, and the Porcupine Fire, in 1911 Ontario; Egan 2009, <http://www.nwccg.gov>) mandated fire suppression to contain all fires by 10:00 of the following day. This policy was in effect until 1964 when the positive benefits of natural and prescribed fires were formally recognized in the Wilderness Act, after having been demonstrated by research (Busenberg 2004). Similarly, in 1968 the National Park Service changed its policy to recognize the natural role of fire (Busenberg 2004).

Even with less emphasis on suppression, wildfire-related expenditures have continued to increase, yet the average area burned nationally has not decreased (Westerling et al. 2006, NICC 2013, Ellison et al. 2015). Some argue that throughout the United States, the protection of buildings has now become the primary activity of wildland fire agencies because scattered development patterns place so many homes and other buildings at risk (Pincetl et al. 2008). Indeed, on average, 2677 buildings (residences, outbuildings, and commercial) were lost to wildfires every year in the conterminous United States from 1999 to 2003 (NICC 2013). However, this number is much lower than the number of buildings exposed to wildfires, i.e., those located within fire perimeters. When wildfires occur in the WUI, typically only a small proportion of the buildings within the fire perimeter are lost (Alexandre et al. 2015), raising the question why some buildings burn and others do not.

Because wildfires are shaped by climate, topography, and vegetative fuel, and because vegetation is the only factor that can be directly managed (Husari et al. 2006), fuel manipulation is seen as the most effective way to influence future wildland fires (Husari et al. 2006). Thus in 2000, the U.S. National Fire Plan (NFP) established “a long-term hazardous fuels reduction program to reduce the risks of catastrophic wildland fire to communities” (<http://www.forestsandrangelands.gov/>) and mandated to focus fuel management funds on the WUI (Husari et al. 2006). However, NFP’s implementation resulted in only a small proportion of the hazardous fuel reduction treatments within WUI areas, and only 50%

guided by community wildfire protection plans (CWPPs; Schoennagel et al. 2009). This is unfortunate because it matters greatly where WUI fuel treatments are located in relation to buildings (Bar-Massada et al. 2011a). Irrespective of the location of fuel treatment, focusing solely on fuels may be insufficient because where buildings are located in relation to other buildings is more important in explaining building loss than are vegetation patterns (Syphard et al. 2012, Alexandre et al. 2016). In fact, at the building level, the most effective actions are to reduce woody cover by up to 40% immediately adjacent to buildings and ensure that vegetation does not overhang or touch the building (Syphard et al. 2014). However, at the landscape level, building density and distance to major roads were the strongest explanatory variables of building loss (Syphard et al. 2014). Arrangement and location of buildings are key in determining susceptibility to wildfire in southern California, where property loss is highest at low to intermediate building densities and in areas with short fire return intervals (Syphard et al. 2012). In Australia, a greater proportion of the buildings lost were within 40 m of other buildings (Gibbons et al. 2012). And finally, in southern California and Colorado, topography, the spatial arrangement of buildings, and vegetation connectivity explain a larger portion of the variability in building losses than does vegetation type (Alexandre et al. 2016). However, it is likely that the relationships and dynamics between fuel treatments, building placement, and landscape configuration differ among ecoregions of the United States, in part because their fire regimes vary. Some forest types have historically burned infrequently but with high intensity (Agee 1993), while others have long dry seasons and easily combusted forest floors, burning more frequently but less intensely. For example, the dry ponderosa pine forests have short fire return intervals with frequent, low-severity fire (Allen et al. 2002), while California’s chaparral and southern shrublands have longer fire return intervals, and periodic fires under severe weather conditions (Keeley et al. 2009). Because the drivers of fire occurrence and behavior differ in these two landscapes, they have different fire regimes. The two landscapes also have different building patterns, regulations, and topography. It would be expected that the topography strongly affects building loss to wildfire in a landscape where the topography is variable while in flat areas dominated by grasslands building loss might be more strongly related to building materials or wind intensity. In southern California, strong winds that pass through deep valleys generate extreme fire behavior resulting in a large number of buildings lost to wildfires and likely affecting which buildings are lost. Similarly, in a crown fire regime vs. a low-intensity grassland fire regime, it is likely that vegetation affects building loss differently even if building loss is high in both situations. These examples highlight that there is a need to understand which factors are most important in determining if a building will be lost when a wildfire occurs and how those might vary in different ecoregions.

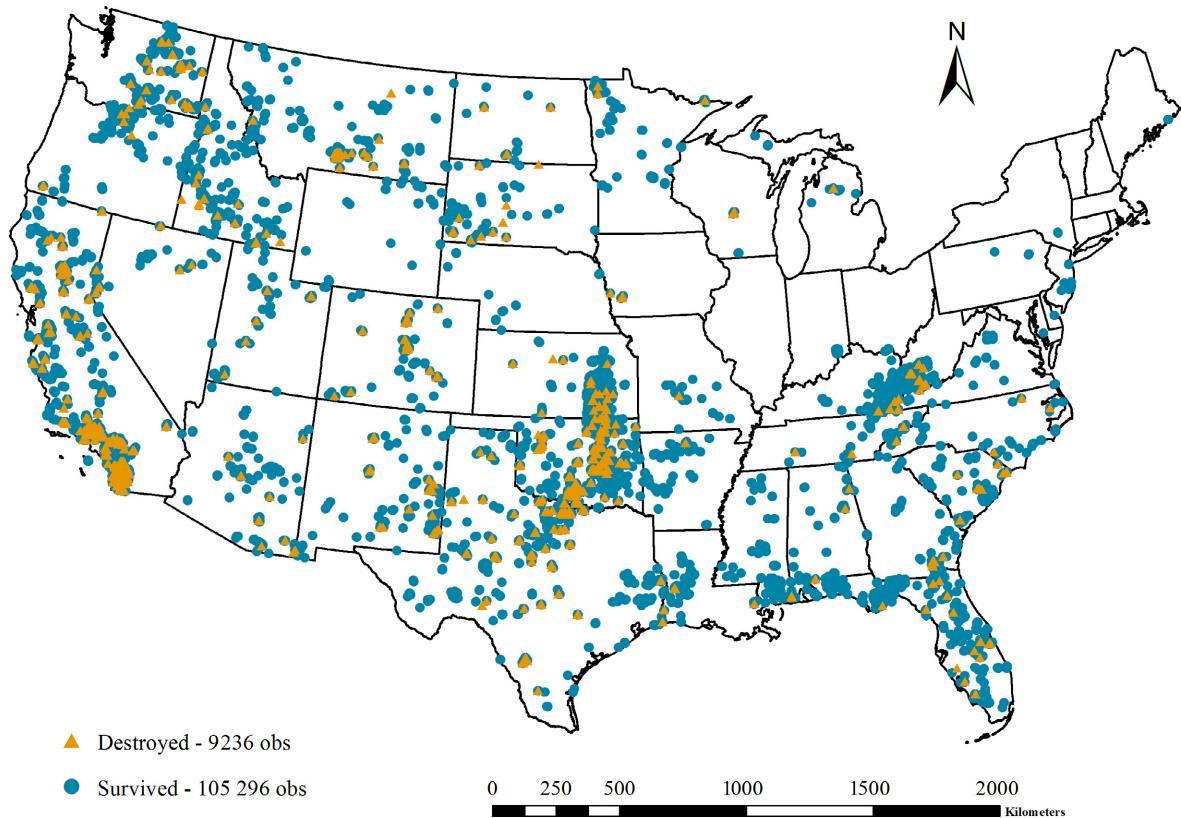


FIG. 1. Distribution of all the digitized buildings (destroyed and survived) that were inside fire perimeters between 2000 and 2010 for the conterminous United States.

In summary, our goal was to identify how vegetation, topography, and the spatial patterns of buildings relate to building loss when a wildfire occurs, and how the relative importance of these factors varies among ecoregions. Specifically, we asked: (1) What factors are related to whether any buildings are lost when a wildfire hits a cluster of buildings? and, (2) What factors are related to the proportion of buildings that are lost within a cluster when at least one building in the cluster is lost?

METHODS

Study area and data: buildings and clusters

We used Google Earth's historical imagery to assess building loss due to wildfires in all fire perimeters in the conterminous United States between 2000 and 2010 recorded in the Monitoring Trends in Burn Severity (MTBS) data set (<http://www.mtbs.gov/> downloaded on 03/05/2012). Google Earth imagery comes from a variety of sources, such as satellites (Landsat, SPOT Image, GeoEye-1, and IKONOS), aerial photography, and even kites and balloons, which means that the spatial and temporal resolution, as well as the number of available historical images, varies by location ([\[com/blog/archives/2014/04/google-earth-imagery.html\]\(http://www.gearthblog.com/blog/archives/2014/04/google-earth-imagery.html\), assessed on Sep/2/2015\).](http://www.gearthblog.</p>
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Within each fire perimeter, we digitized all the buildings that survived the fire (buildings present before and after the fire date), and all that were lost (buildings present before the fire date, but not after). We considered a building to be lost when it was completely removed in the post-fire image. This means that our estimates are conservative, and did not include partial damage or damage that was not visible from the top, such as smoke damage or partial siding melt. In total, we digitized 114532 buildings, of which 9236 were lost (Fig. 1).

We conducted our analysis using the clusters of buildings as our unit of analysis because previous analysis (Alexandre et al. 2015) showed evidence of spatial autocorrelation when buildings were the unit of analysis. By using clusters instead of buildings, we overcame spatial resolution issues and eliminated what would otherwise have been pseudo-replication among individual buildings. We considered buildings to be in the same cluster if 100-m buffers around each building were contiguous (Fig. 2). We applied a distance of 100 m to capture the spatial arrangement of buildings and applied the same distance thresholds as previous studies that looked at building loss and mapped the WUI (Syphard et al. 2007a, 2012, Lampin-Maillet et al. 2010). For each cluster, we

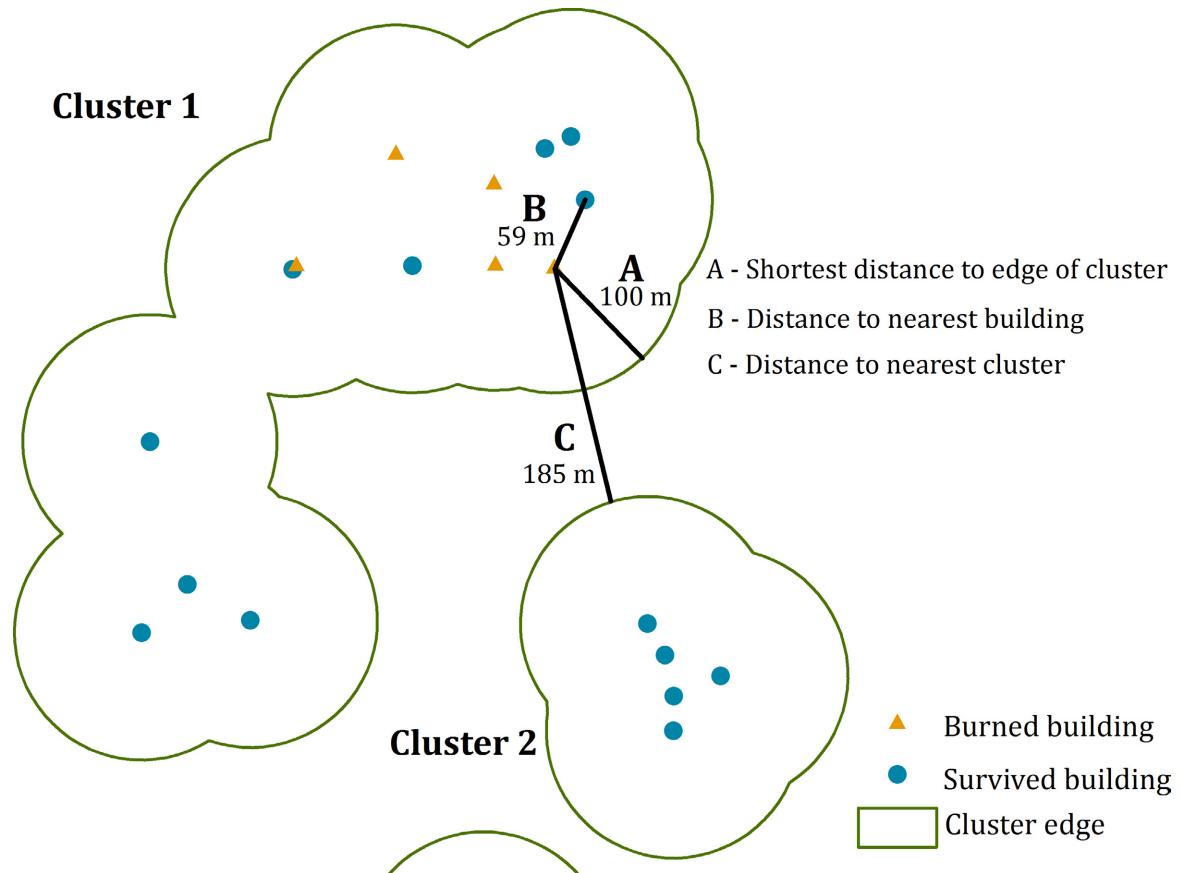


FIG. 2. Example of clusters that were created using a radius of 100 m; cluster 1 contains one example of how the (A) shortest distance to the edge of cluster, (B) shortest distance to the nearest building, and (C) shortest distance to the nearest cluster were calculated.

calculated our independent variables, derived from mapped data, at two scales: (1) within the cluster; and (2) within the surrounding landscape, defined as the area within 2500 m (because 2500 m is the approximate distance the wind might carry an ember; Cohen 2000).

In a preliminary analysis, we observed that including very small clusters had the potential to bias the results (Appendix S1). Therefore, we restricted the analysis to clusters that had, at least, eight buildings. Similarly, for the logistic regression analysis, we examined only clusters with at least eight buildings. Also, we restricted our analyses to ecoregions that had at least 40 clusters and where at least 10% of clusters lost buildings (Table 1).

Ecoregions

We analyzed our data for Omernik level I ecoregions (http://www.epa.gov/wed/pages/ecoregions/na_eco.htm#Downloads, last accessed on 02/20/2015, Fig. 3; Omernik 1987). We assigned clusters to ecoregions based on their location. However, only five ecoregions had enough clusters (>40) for our logistic regression analysis, which accounted for 69% (78961 buildings) of all the

buildings that we digitized, and four ecoregions had enough for our linear regression analysis, which included 67% (77170 buildings) of all buildings digitized (see Table 1 and Appendix S2 for total number of digitized buildings).

Vegetation data

The 2006 National Land Cover Database (NLCD 2006) is the highest resolution, consistent land cover classification scheme available for the whole conterminous United States at a spatial resolution of 30 m, based on Landsat satellite data ca. 2006. Since our study area was the conterminous United States and our fire data was from 2000 to 2010, we used NLCD 2006 data as a proxy for the horizontal distribution of fuels during that period. Due to the categorical nature of this variable, and for effective statistical analysis, we reclassified the data for deriving fuels metrics at both the cluster level and landscape level analysis. To capture the vegetation type for each building, we reclassified land cover into four groups: non-flammable, forest, shrubs/scrubs, and grassland/pasture/hay (Appendix S3).

We were also interested in fuel configuration and connectivity in the area surrounding a building, which are

TABLE 1. Total number of digitized buildings and the total number of clusters with more than eight buildings in each ecoregion.

	Total number of clusters (logistic regression)	Clusters with at least one building lost (linear regression)	Percentage of clusters with buildings lost (%)	Total number of buildings within fire perimeters	Buildings lost	Percentage of buildings lost (%)
Conterminous United States	2029	547	27	80393	7171	9
North American deserts	92	17	18	1791	64	4
Mediterranean California	860	298	35	53093	5301	10
Southern semiarid highlands†	8	3	38	328	160	49
Temperate Sierras†	20	1	5	632	4	0.6
Tropical wet forests†	4	1	25	152	2	1
Northern forests†	13	1	8	274	1	0.4
Northwestern forested mountains	163	49	30	4504	800	18
Marine West Coast forest†	4	2	50	46	23	50
Eastern temperate forest	546	53	10	12806	216	2
Great Plains	319	122	38	6767	600	9

†Ecoregion not included in the regression analyzes because either they had <40 clusters within fire perimeters, or <10% of the clusters with at least one building lost.

relevant to fire spread, and used landscape metrics to capture this. Because this analysis focused on fire spread, we reclassified land cover into three groups: highly flammable, flammable, and non-flammable (Appendix S4). Shrublands can support intense fires that may produce firebrands, and grassland areas produce less intense, fast-moving fires. Therefore, we included evergreen forest, mixed forest, shrub/scrub, and grassland/herbaceous classes in the highly flammable class. Deciduous forest, pasture/hay, and crops are vegetation types that can support fire spread in some seasons but are less likely to produce a fire that will ignite a building, so we classified them as flammable. The remaining NLCD classes are not flammable due to their lack of vegetation or because their moisture content is too high to produce a fire, and these were classified as non-flammable (Appendix S4). We derived landscape metrics using Fragstats, a software for spatial analysis (McGarigal et al. 2012), for the area within 2500 m from each cluster. We calculated one landscape-scale metric, contagion (Fragstats name: CONTAG), and two class-scale metrics; percentage of land for each class (PLAND_i), and connectivity (CONNECT_i; see McGarigal and Marks 1995 for definitions).

In addition to the NLCD, we tested in a preliminary analysis existing vegetation type (EVT), canopy bulk density (CBD), and fuel characteristic classification system

fuelbeds (FCCS) at the building level, from LANDFIRE version 1.0.5 (<http://www.landfire.gov>) as proxies for flammable vegetation and fuels around each building. However, we found some inconsistencies in the CBD data set and neither EVT nor FCCS were selected as significant variables when we ran preliminary models. For these reasons, we did not include EVT, CBD, and FCCS in the full analysis.

Topographic data

In our statistical models, we included elevation, slope, topographic position index (TPI), road density, and southwestness derived from aspect (Syphard et al. 2007b). Topography affects fire behavior due to the micro-weather conditions created by elevation and aspect (e.g., moisture gradients), and topographic features such as narrow valleys or steep slopes influence fire spread. Topography also affects fires indirectly by determining 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).

Slope and elevation are part of the LANDFIRE (<http://landfire.cr.usgs.gov/viewer> assessed on 03/05/2015, 30-m resolution) data set and derived from the National Elevation Data set (NED, ned.usgs.gov). Topographic

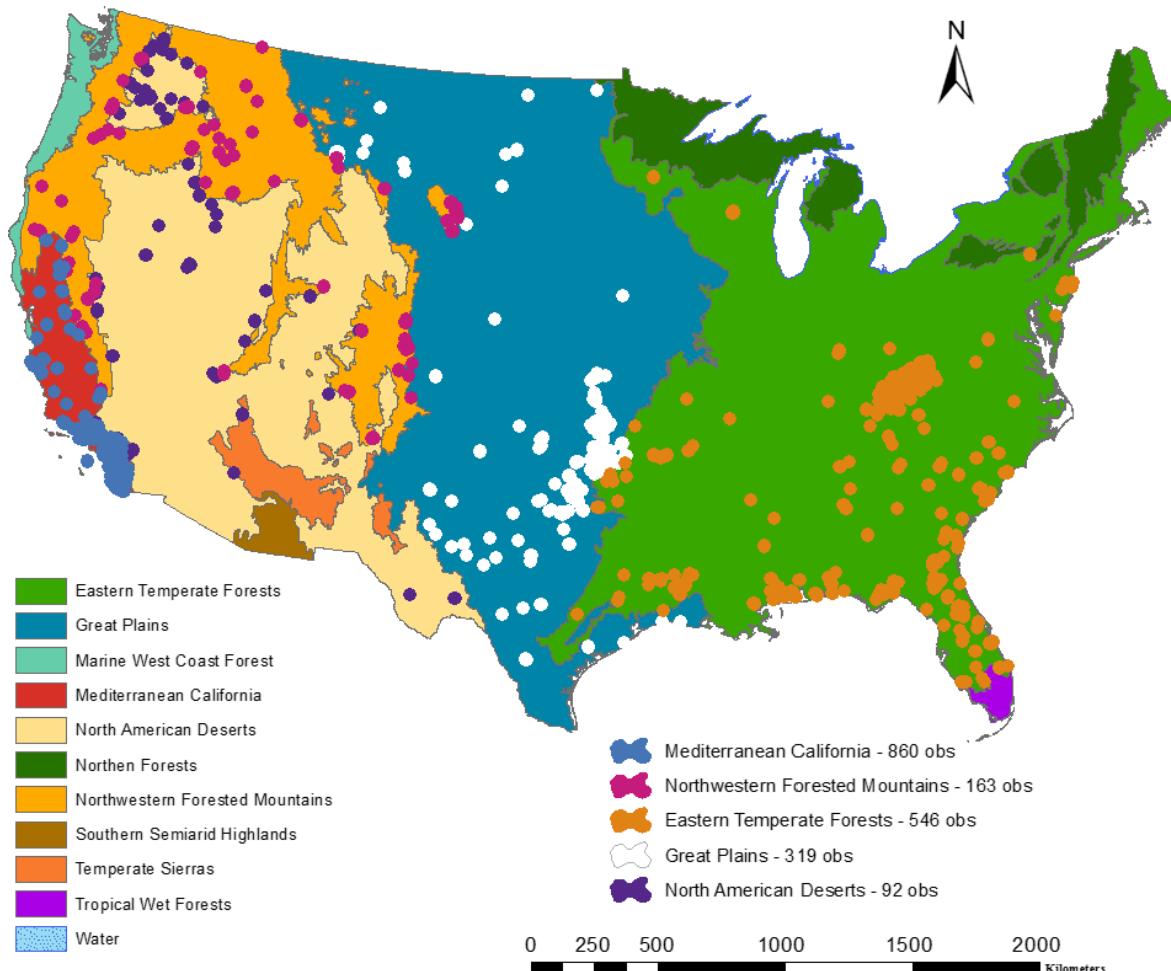


FIG. 3. Map of Omernik ecoregions for the conterminous United States and cluster distribution per ecoregion.

position index is a categorical variable that refers to the location of a building on the landscape (valley, lower slope, gentle slope, steep slope, upper slope, ridge). We calculated the topographic position index from the LANDFIRE elevation data 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). The algorithm results in a categorical raster that contains values between 1 and 6 to represent the topographic position:

- (1) Valley: $TPI \leq -1$ standard deviation (SD)
- (2) Lower Slope: $-1 SD < TPI \leq -0.5 SD$
- (3) Flat Slope: $-0.5 SD < TPI < 0.5 SD$, slope $\leq 5^\circ$
- (4) Middle Slope: $-0.5 SD < TPI < 0.5 SD$, slope $> 5^\circ$
- (5) Upper Slope: $0.5 SD < TPI \leq 1 SD$
- (6) Ridge: $TPI > 1 SD$

Each building acquired the TPI value of the raster cell that intersected the building. Each cluster assumed the

majority value of the buildings in the cluster. Due to a biased distribution of values toward ridges or valleys, we reclassified the remaining values to be either valleys or ridges, having a simple classification of two categorical values. Values 2 and 3 were reclassified to 1 (valley). Values 4 and 5 were reclassified to 6 (ridge).

Road density is a proxy for both human presence on the landscape and access to buildings. We downloaded road data from the U.S. Census Bureau website (www.census.gov downloaded on 04/14/2014) and calculated road density by dividing total road length within each cluster by cluster area.

Spatial arrangement of buildings

Because research suggests 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), we calculated seven variables to quantify the spatial pattern of buildings within clusters. For each cluster we calculated (1) the area, (2) the number of buildings, (3)

TABLE 2. List of variables included in logistic and linear regression models and their sources.

Variable	Description	Source
Land cover	see Appendices S1 and S2 for details on cover classes and their reclassification	NLCD 2006
Percentage of land/class	see Fragstats literature	Fragstats (McGarigal and Marks 1995)
Connectance/class		Fragstats
Connectance		Fragstats
Contagion index		Fragstats
Elevation	mean elevation within each cluster, 30 m resolution	Landfire DEM (http://www.landfire.gov)
Slope	mean slope calculated in degrees, 30 m resolution	Derived from DEM
Topographic position index	majority class within each cluster, six classes, extension tool on ArcMap	Jenness 2006
Southwestness	mean of cos(ASP) within each cluster	calculated in this study
Road density	total length inside cluster/total area	2010 TIGER/Line Shapefiles (https://www.census.gov/cgi-bin/geo/shapefiles2010/file-download)
Cluster area	cluster area (m ²)	calculated in this study
Number of buildings within cluster	total number of buildings within the cluster	calculated in this study
Building density	number of buildings within a cluster divided by the cluster area	calculated in this study
Building dispersion	standard deviation of the distance among buildings within a cluster divided by the mean distance among buildings within the cluster	calculated in this study
Average distance to cluster edge	mean distance from each building to the edge of the cluster	calculated in this study
Average distance to nearest building	mean distance to the nearest building	calculated in this study
Average distance to nearest cluster	average distance to the nearest cluster	calculated in this study

building density (Eq. 1), (4) building dispersion (Eq. 2), (5) the average distance to the edge of the cluster, (6) the average distance to the nearest building, and (7) average distance to the nearest cluster (Fig. 2). We calculated building density and building dispersion using the following equations:

$$\text{Building density} = \frac{\text{number of buildings within a cluster}}{\text{cluster area (ha)}} \quad (1)$$

$$\text{Building dispersion} = \frac{\text{st dev. of dist. among buildings within a cluster}}{\text{mean distance among buildings within a cluster}} \quad (2)$$

For a complete list of all the variables used in our analysis, see Table 2.

Statistical analysis

Our conceptual model shows the factors that we expected to have different contributions depending on the location (Fig. 4). Therefore, we selected variables that had either direct or indirect relationships with building loss in previous studies; in particular, studies regarding fire behavior, and investigations specific to identifying the

causes of building loss. Due to the national scale of our analysis, our methods are a starting point for developing a theory regarding these expected regional differences.

To answer our first question, i.e., what factors are related to whether any buildings are lost when a wildfire hits a cluster of buildings, we used logistic regression (Hosmer and Lemeshow 2000). We selected the best model based on an exhaustive search of all possible combinations of explanatory variables and ranked models by their Bayesian information criterion (BIC; Schwarz 1978) while constraining the maximum number of variables in the models based on the number of observations within a given ecoregion. We conducted the search with `bestglm` (McLeod and Xu 2011) in the statistical software R (R Core Team 2014) and examined the top 20 models in detail. For simplicity, we report the coefficients for the best model for each ecoregion for each statistical approach (logistic or linear), and how frequently each explanatory variable was present in the top 20 models. The notion of “importance” is a nontrivial one and long debated in statistics, with no consensus on the best way to measure importance. For that reason, we opted for a combination of methods such as including variable frequency, a more informative measure of variable importance than presence in the top model only, and the area under the curve (AUC) as ways of indicating the potential value of explanatory variables. We checked for spatial

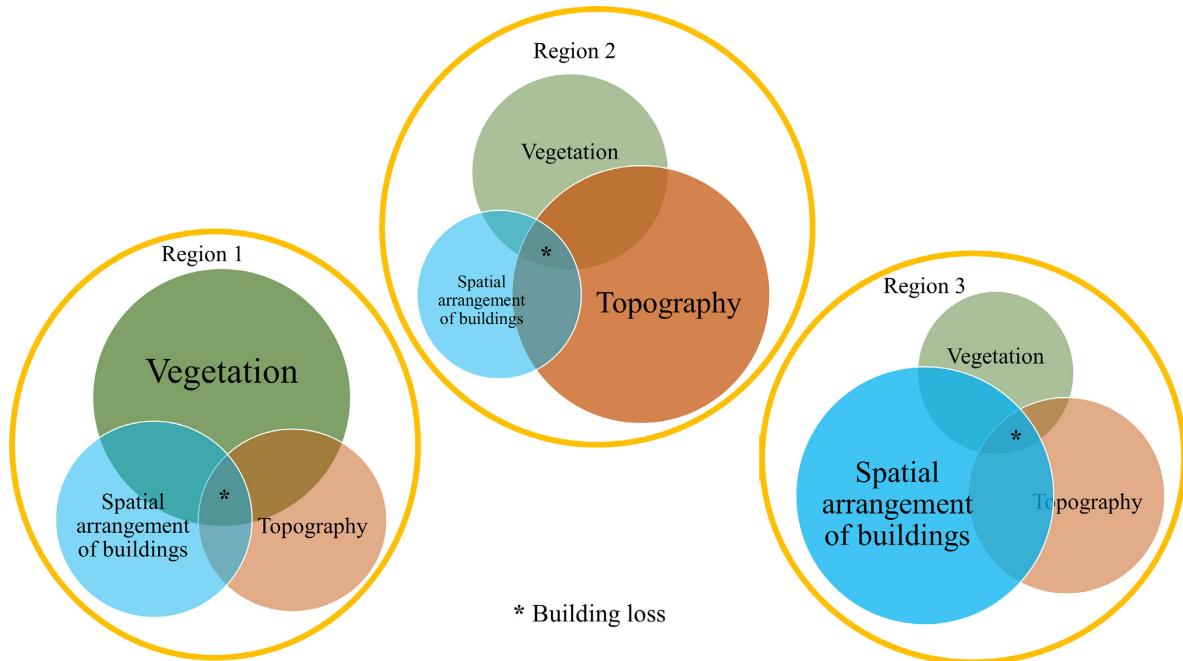


FIG. 4. Vegetation, topography, and the spatial arrangement of buildings are all associated with building loss but play a greater or lesser role in different regions.

autocorrelation in the residuals of the top model in each ecoregion using semivariograms (R package *geoR*; Ribeiro and Diggle 2001), and found no evidence of spatial autocorrelation. To measure the discriminatory ability of the models, we calculated AUC of the receiver operating characteristic (ROC) curve (R package *ROCR*; Sander et al. 2005). In addition, for each ecoregion, we performed cross-validation to test for robustness of the conclusions based on AUC. We randomly removed 20% of the observations in a given ecoregion, performed model selection with the remaining 80%, and calculated AUC for the best model using the removed data. We repeated these steps 10 times for each ecoregion.

To answer our second question, i.e., what factors are related to the proportion of buildings that are lost within a cluster where at least one building is lost, we modeled the proportion of buildings lost within each cluster using multiple linear regression models (Freedman 2009). We conducted model selection based on an exhaustive search of all possible combinations of explanatory variables using the R package *bestglm* (McLeod and Xu 2011) and ranked models based on the BIC (Schwarz 1978). We again observed how frequently each variable was selected in the top 20 models to quantify the relative importance of the individual variables. We checked for spatial autocorrelation in the residuals of the top model in each ecoregion using semivariograms (R package *geoR*; Ribeiro and Diggle 2001), and found no evidence of spatial autocorrelation. In addition, we assessed model assumptions, e.g., normality and homoscedasticity, as appropriate. Finally, to measure the ability of the models to explain

the variability in the data, we calculated the adjusted R^2 for the top model in each ecoregion.

Although we expected that there would be differences in the importance of variables among ecoregions, we conducted a preliminary analysis in which we used all the observations regardless of the ecoregion to which they belonged (a “national model”; Appendices S5 and S6). However, because we were interested in the differences among ecoregions, we conducted our analyses at the ecoregion level.

RESULTS

In total, there were 16595 clusters of buildings within fire perimeters, of which 2029 contained, at least, eight buildings and these included 70% of all digitized buildings. We included 1980 of these clusters for the logistic regression analysis, categorizing them according to whether any building was lost or not, and used that binary variable as the response variable. As a robustness check, we also ran our logistic regression models for all clusters with at least four buildings, and results were very similar to those for clusters with at least eight buildings (those results are not shown). For the linear regression, we included only those 547 clusters that had, at least, one building lost. The response variable for the linear regression was the proportion of buildings lost within the cluster (Table 1).

Likelihood of any wildfire losses: Logistic regression

Vegetation.—We included seven variables related to vegetation and fuels in our analysis: land cover, contagion index, connectivity of the landscape,

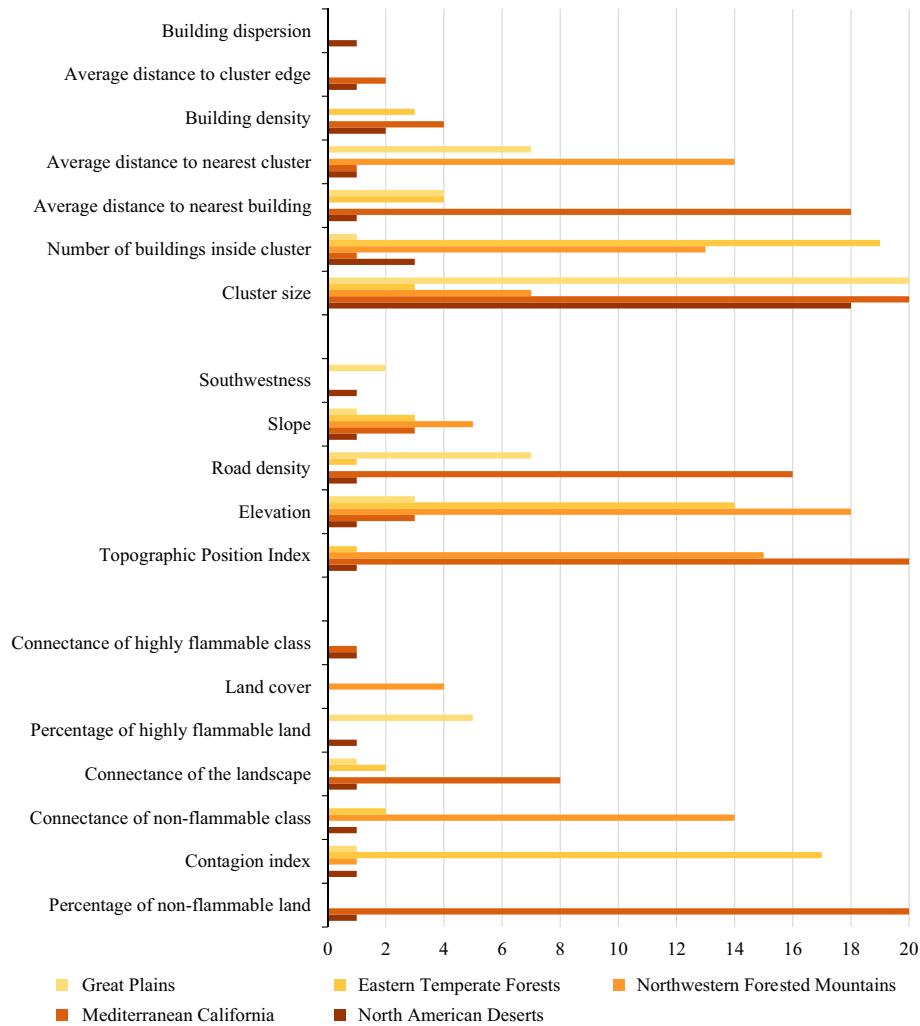


Fig. 5. Frequency of variables in the top 20 models of our logistic regressions.

connectivity of highly flammable and non-flammable land, and percentage of highly flammable and non-flammable land. In the preliminary national model, we found significant interactions between ecoregion and some variables (results shown in Appendices S5 and S6), indicating that the effect of these variables differed among ecoregions. In the models for the different ecoregions, overall, the frequency of vegetation-related variables in the top 20 models was low. The variable that appeared most frequently in the top 20 models was percentage of non-flammable land in the mediterranean California ecoregion (Fig. 5) with a negative effect, meaning that places with a higher percentage of urban area were less likely to be affected by wildfires (Table 3). Contagion index and connectivity of non-flammable land were the next most frequent vegetation variables and occurred in eastern temperate forests and the Northwestern forested mountains (Fig. 5). In both ecoregions, the effect was negative, meaning that dispersed urban areas and fragmented landscapes were

more likely to be associated with building losses to wildfires. For the remaining ecoregions, the frequency of vegetation related variables was always less than eight times out of 20.

Topography.— We included five variables related to topography in our analysis: elevation, slope, southwestness, topographic position index (TPI), and road density. Topographic position index, elevation, and road density appeared more frequently in the models of mediterranean California, Northwestern forested mountains, and eastern forested mountains. Topography-related variables were selected in the top models for mediterranean California and Northwestern forested mountains, always with positive effects, meaning that clusters located at the tops of ridges, at higher elevations and with higher road density were more likely to be affected if a wildfire occurs. In the remaining ecoregions, Great Plains and North American deserts, topography-related variables were present in fewer than seven of the top 20 models.

TABLE 3. Coefficients, standard errors (SE), *P* values, and area under the curve (AUC) values for 10-fold cross-validation for the top logistic model in each ecoregion.

	Coefficient	SE	Pr(> z)	AUC
North American deserts				
Intercept	-3.56	0.74	< 0.001	0.802 (0.56–0.88, mean 0.69)
Cluster area	0.07	0.02	0.007	
Connectivity of the landscape	0.04	0.02	0.030	
Mediterranean California				
Intercept	-2.13	0.28	< 0.001	0.766 (0.70–0.82, mean 0.76)
Cluster area	0.03	0.00	< 0.001	
Road density	9.94×10^{-4}	0.00	0.004	
Distance to nearest building	0.01	0.00	0.001	
Topographic position index; top ridges	0.64	0.17	< 0.001	
Percentage of non-flammable land	-0.02	0.01	< 0.001	
Northwestern forested mountains				
Intercept	-2.97	0.73	< 0.001	0.878 (0.70–0.93, mean 0.81)
Number of buildings in the cluster	0.04	0.01	0.002	
Distance to nearest cluster	-1.52×10^{-3}	0.00	0.157	
Elevation	1.01×10^{-3}	0.00	0.004	
Topographic position index, top ridges	1.33	0.46	0.004	
Connectivity index of non-flammable class	-0.07	0.03	0.033	
Eastern temperate forests				
Intercept	-1.31	0.55	0.018	0.727 (0.68–0.84, mean 0.75)
Number of buildings in the cluster	0.02	0.00	< 0.001	
Contagion index	-0.03	0.01	0.005	
Great Plains				
Intercept	-1.30	0.21	< 0.001	0.669 (0.62–0.75, mean 0.69)
Cluster area	0.04	0.01	< 0.001	

Spatial arrangement of buildings.—Of the three types of variables, the spatial arrangement variables were most frequent in the top 20 models (Fig. 5). We included seven variables related to the spatial arrangement of buildings in our analysis: cluster area, the number of buildings in the cluster, average distance to the nearest building, average distance to the nearest cluster, average distance to cluster edge, building density, and building dispersion. Cluster area was the most frequently included variable (selected in all 20 top models) in the models of mediterranean California and Great Plains and was present in 18 of the 20 top models of the North American deserts (Fig. 5). All three coefficients had a positive sign meaning that larger clusters were more strongly associated with the loss of at least one building, mostly likely because more buildings are exposed (Table 3). The number of buildings in the cluster and average distance to the nearest building were the second most frequent variables and were present in the top model of mediterranean California, Northwestern forested mountains, and eastern temperate forests. In both Northwestern forested mountains and eastern temperate forests, the higher the number of buildings in the cluster, the more likely it was that at least one building was lost. In mediterranean California, the average distance to the nearest building had a positive effect, meaning that the farther apart the buildings are, the more likely they are to be affected. In the Northwestern forested mountains, the average distance to the nearest

cluster had a negative sign meaning that clusters that are closer to other clusters are more likely to be affected by wildfires (Table 3). All other variables were present in fewer than seven of the 20 top models.

Extent of wildfire losses: Linear regression

Vegetation.—The vegetation variables that occurred most frequently in all 20 top models were percentage of highly flammable land and connectivity of highly flammable land, followed by the contagion index (14 out of 20 top models). Vegetation variables were most frequently selected in two ecoregions: the Northwestern forested mountains and the Eastern temperate forests (Fig. 6). In both ecoregions, clusters that were located in landscapes with a higher percentage of flammable land but with lower connectivity, i.e., fragmented landscapes, were more likely to have a higher proportion of buildings lost (Table 4). In mediterranean California and the Great Plains ecoregions, vegetation-related variables were present fewer than seven times in the 20 top models (Fig. 6).

Topography.—The most frequently included topography variables were elevation, topographic position index, and road density (Fig. 6). In the mediterranean California ecoregion, clusters located at higher elevations were more likely to have higher proportions of buildings lost

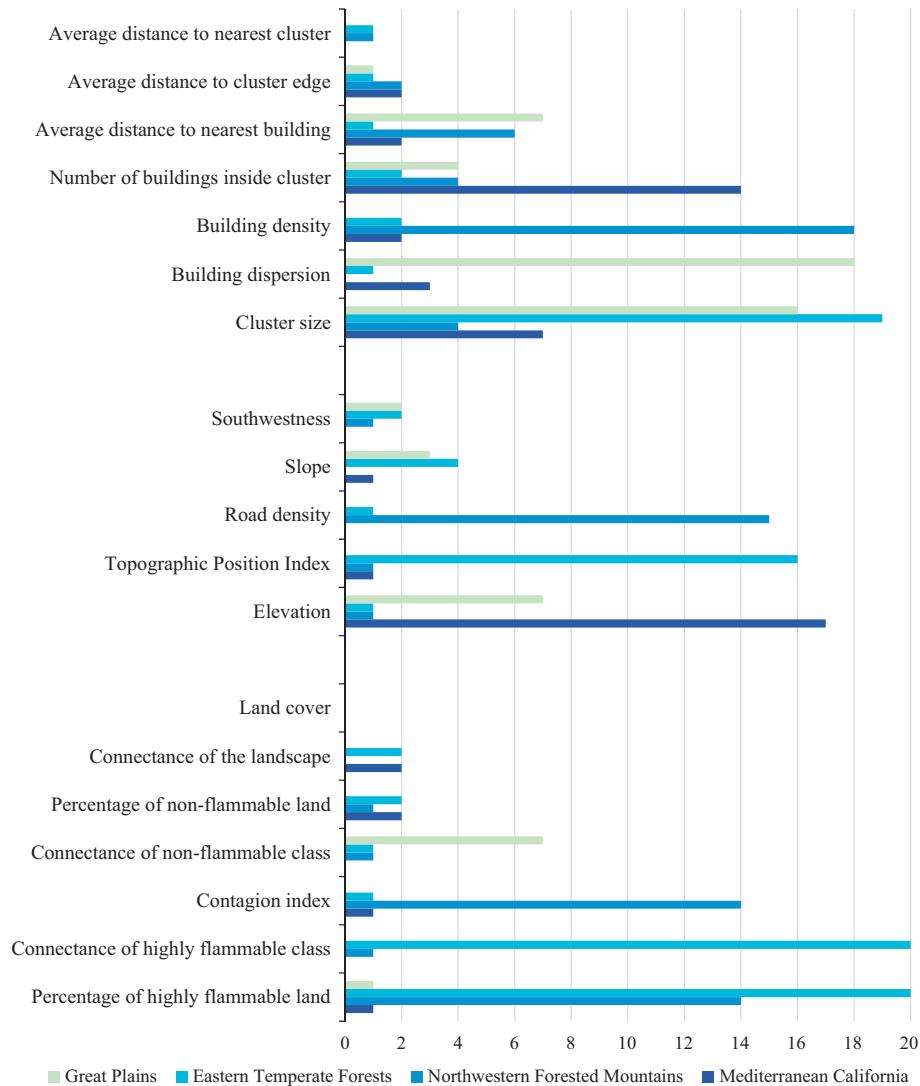


Fig. 6. Frequency of variables in the top 20 models of our linear regressions.

(Table 4). In the Northwestern forested mountains ecoregion, clusters with lower road density were more likely to have higher proportions of buildings lost (Table 4). In the Eastern temperate forest, clusters on ridges were more likely to have higher proportions of buildings lost (Table 4). In the Great Plains, topography variables were less frequent in the top models, and all topography variables occurred fewer than seven of the top 20 models (Fig. 6).

Spatial arrangement of buildings.—Variables related to the spatial arrangement of buildings were present more frequently than topography- or vegetation-related variables in the top 20 models, and in all four studied ecoregions. Cluster area was the most frequent variable in the Eastern temperate forests and the second-most frequent in the Great Plains. In both cases, smaller clusters were more likely to have a higher proportion of

buildings lost (Table 4). Building dispersion was frequently present in the models for the Great Plains, where clusters with lower dispersion values were more likely to have a higher proportion of buildings lost. In the Northwestern forested mountains, building density was the most frequent spatial arrangement variable, and clusters with lower density had a higher proportion of buildings lost (Table 4). In mediterranean California, variable frequencies were less consistent among the top 20 models, but the number of buildings in the cluster was selected in 14 of the 20 top models (Fig. 6), and clusters with fewer buildings were more likely to have a higher proportion of buildings lost (Table 4).

Model performance.—The AUC values for the logistic regression for each top model in each ecoregion ranged from 0.66 to 0.88 (Table 3). For the linear regression the adjusted R^2 values were generally low, ranging from 0.20

TABLE 4. Coefficients, standard errors, and *P* values for the top linear model in each ecoregion.

	Coefficient	SE	Pr(> t)	Adjusted <i>R</i> ²
Mediterranean California				
Intercept	3.24	0.27	< 0.001	0.20
Number of buildings in the cluster	-0.35	0.05	< 0.001	
Elevation	0.02	0.01	0.003	
Northwestern forested mountains				
Intercept	0.21	1.89	0.910	0.34
Building density	-0.95	0.24	< 0.001	
Road density	-0.10	0.03	0.004	
Contagion index	-0.78	0.25	0.003	
Percentage of highly flammable land	1.05	0.35	0.005	
Eastern temperate forests				
Intercept	5.48	0.47	< 0.001	0.67
Cluster area	-1.15	0.12	< 0.001	
Topographic position index, top ridges	0.83	0.25	0.002	
Percentage of highly flammable land	0.33	0.09	0.001	
Connectivity of highly flammable class	-1.18	0.30	< 0.001	
Great Plains				
Intercept	7.68	1.19	< 0.001	0.30
Cluster area	-0.60	0.09	< 0.001	
Building dispersion	-4.15	1.57	0.009	

to 0.67 (Table 4). Cross-validation for each ecoregion yielded averaged AUC values that were close to the ones obtained in the top model for each ecoregion (Table 3), indicating that our results were robust.

DISCUSSION

As we expected, the role of vegetation, topography, and the spatial arrangement of buildings differed greatly among ecoregions. However, for both questions, i.e., whether any buildings were lost, and what proportion of buildings was lost, topography and the spatial arrangement of buildings were more frequently selected than vegetation-related variables.

People are moving near wildland vegetation and into landscapes where fire is a reality, even though fire frequency varies depending on the ecosystem (Nowak and Walton 2005, Hammer et al. 2007, Gude et al. 2008). More people means a higher probability for human-caused ignitions (Bar-Massada et al. 2009, Price and Bradstock 2014), creating a positive feedback cycle and thus a coupled human–natural system. Given the importance of the spatial arrangement of buildings in both buildings lost and human ignitions, ignition prevention programs may be an integral component for reducing future buildings loss (Abt et al. 2015, Chas-amil et al. 2015, Syphard and Keeley 2015).

For both logistic and linear regressions, vegetation variables related to landscape metrics, such as connectivity and percentage of highly flammable land, were important. For example, the top model for the North American deserts ecoregion identified cluster area and landscape connectivity as the two main drivers of wildfire effects on communities. Although fire behavior in

grasslands is not as well studied as in other vegetation types, some studies in shrubland-dominated areas, such as California, have shown us that crown fires in forests are not required for building loss to occur (Brooks and Matchett 2006, Syphard et al. 2011, Gray and Dickson 2015). Furthermore, invasive annual grasses in the desert are providing fuel connectivity to support fires where they had been absent historically, raising ecological concern (Gray and Dickson 2015).

Topography-related variables were present in the top logistic models of two ecoregions and the top linear models in three ecoregions. For both mediterranean California and the Northwestern forested mountains, clusters located at higher elevations or on top of ridges were more likely to have lost buildings. That supports other studies done in California where topography was an important driver of extreme fire behavior (Dillon et al. 2011, Flatley et al. 2011, Syphard et al. 2012). The Northwestern forested mountains is a very diverse ecoregion. It contains the highest mountain in North America and the most diverse mosaic of ecosystem types, such as mountains and plateaus separated by valleys and lowlands. Topography is the common denominator for such diversity, and clusters in northwestern forested mountains that were located at higher elevations or at the tops of ridges were more likely to be affected by wildfire.

High road density increased the probability that any building was lost in mediterranean California, but it was negatively correlated with the proportion of buildings lost in the Northwestern forested mountains. Mediterranean landscapes are often heavily settled, and roads are a proxy of human activity, which is linked to a higher probability of ignitions (Syphard et al. 2007b,

Bar-Massada et al. 2011b). In the Northwestern forested mountains, however, lower road density makes areas harder to access when fighting fires, leading to a higher proportion of buildings lost.

The spatial arrangement of buildings was important in every top logistic or linear model. This is one of the most striking results, given the predominant focus in fire management on vegetation as a risk factor. Independent of the ecoregion's characteristics, the location of the cluster in relation to other clusters and how far buildings were from other buildings had a clear association with building loss in case of wildfire. The most prominent variable was cluster area, followed by the number of buildings in the cluster, but the signs of the coefficients for both variables varied depending on the type of analysis. When explaining if any building was lost, larger clusters with more buildings were more likely to be affected by a wildfire. However, when explaining what proportion of buildings was lost, smaller clusters with fewer buildings were more likely to lose a higher proportion. When building density is higher, there is a higher probability that once a wildfire hits one building, the fire will progress from building to building. Indeed, in Australia, being close to other buildings increases a building's chance of being lost to wildfires (Gibbons et al. 2012). Also, smaller clusters are more likely to contain buildings lost because they have more edge and thus more buildings directly exposed to wildland vegetation.

Finding that smaller, denser clusters are more likely to be affected by wildfires poses a land-use dilemma because conservation strategies seek to cluster buildings to minimize the human footprint on the landscape (Theobald et al. 1997, Gonzalez-Abraham et al. 2007). Furthermore, it is cheaper to protect buildings in groups rather than each individually (Bar-Massada et al. 2011a). The question is what size a cluster should be to optimize both conservation and fire risk reduction goals. The relationships between building density and fire risk are non-linear, and fire risk decreases rapidly above a housing density threshold (Syphard et al. 2012), but at such high housing density values, conservation options are limited because space for natural habitat is limited. At low to medium housing densities, clustering would be advantageous for conservation but appears to be problematic for fire risk reduction.

Both top models for the Great Plains ecoregion contained only variables related to the spatial arrangement of buildings, whereas topography, vegetation, or both were also important in the other ecoregions. The potential natural vegetation of the Great Plains are grasslands, and the climate is dry and continental, characterized by short, hot summers and long, cold winters, high winds, and periodic, intense droughts and frosts. High winds might be one explanation of why so many wildfires result in building loss in the Great Plains. Out of all ecoregions, the Great Plains had the highest proportion of clusters where at least one building was affected (122 out of 319).

When modeling if any building was lost, only cluster area was significant and larger clusters were more likely to have at least one destroyed building in the event of a wildfire. The topography in the Great Plains generally consists of mild slopes, with a very low range of variation. Therefore, it is not surprising that topography was not present in the models. Similarly, vegetation, although certainly important to carry wildfires, was not variable enough to be included in the models. However, low AUC and adjusted R^2 values suggest that some important variables were missing.

Caveats

Wildland fires and building loss are complex processes. Any modeling study has to be selective regarding the variables that are included, and most modeling studies are limited by what data is available. Both were the case in our study. We were selective and decided to focus our models on variables that determine whether a building is lost once a fire occurs, rather than variables that determine if a fire will occur. For example, we did not include information on the types of ignitions, i.e., whether fires were human-related. The reason was that while ignition sources vary substantially among ecoregions and the source of ignitions may affect greatly where fires occur (Bar-Massada et al. 2012), and thus important to know for ignition prevention programs (e.g. Syphard and Keeley 2015), ignition sources matter little for the question of building losses. Similarly, socioeconomic characteristics of the population may affect ignition sources. However, there is no clear pattern linking economic status and wildfire potential (Poudyal et al. 2012), and modeling wildfire likelihood was not our objective.

There were also other types of data that we would have liked to include in our models, but that were not available for the entire United States, and these were data on building materials, fine-scale weather patterns, and fire suppression efforts. Both experimental studies, and post-fire analyzes (Cohen 2000, Nowicki and Schulke 2002, Quarles et al. 2010) highlight that building materials greatly affect which buildings are lost when a fire occurs, but obtaining information on building materials for all the buildings that we digitized was not possible. Fine-scale weather information can also affect whether a building will be lost, and topography is only a proxy for fine-scale weather patterns. However, the weather data that was available nationwide was uniform within each fire area, and that means that it would not have been helpful in our models. Fire suppression efforts are often explicitly targeted to protect houses, thus directly affecting which buildings are lost during a fire. However, there is no consistent data on fire suppression efforts at the national scale, which is why we were not able to include that variable in our models. Finally, in addition to missing explanatory variables, our response variable was also imperfect because some buildings may have been damaged but not lost. Because we used satellite

imagery, we could only identify buildings that were completely lost, and that may have underestimated the effects of fires. Having said that, our models had high explanatory power, as highlighted by the AUC values, despite these limitations, and provided interesting and informative results. We strongly recommend that our models should be validated in subsequent studies with different data. Without such validation, our conclusions need to be carefully interpreted, and our results should not be extrapolated outside the time frame and locations of our study.

CONCLUSIONS

The most important message from our results is that topography and building arrangements strongly affect which buildings are lost, but that the relative importance of variables varies considerably among ecoregions, suggesting that policies and management efforts need to be regionally tailored, as the National Science analysis for the cohesive strategy strongly suggest in their report (<http://cohesivefire.nemac.org/option/6> assessed on 10 October 2015).

Although vegetation may be the most obvious and manageable aspect of wildfire risk that managers can address, fuel treatments are only a partial and short-term solution, and insufficient to address the other sources of fire risk to buildings, as our models clearly show. The challenge is that factors such as topography and building patterns cannot be changed after buildings are in place, and need to be accounted for when urban planners make community-wide planning, subdivision layout, or building siting decisions. We suggest that a better understanding how different factors contribute to the risk that a building will be lost in a wildfire, as we present here, will allow policy makers, planners, and resource managers to develop long-term solutions to reduce fire risk to buildings and make communities more fire-adapted.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online at: <http://onlinelibrary.wiley.com/doi/10.1002/eap.1376/supinfo>

DATA AVAILABILITY

Data associated with this paper have been deposited in Dryad: <http://dx.doi.org/10.5061/dryad.h1v2g>