Journal of Environmental Management 347 (2023) 118960

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

Using high-resolution land cover data to assess structure loss in the 2018 Woolsey Fire in Southern California

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ARTICLE INFO

Handling Editor: Dr. Lixiao Zhang

Keywords:
Fire
Housing
Risk
Los Angeles
Wildland urban interface

ABSTRACT

There are growing concerns about increases in the size, frequency, and destructiveness of wildfire events. One commonly used mitigation strategy is the creation and maintenance of defensible space, a zone around buildings where vegetation is managed to increase potential for structures to survive during wildfires. Despite widespread acceptance and advocacy of defensible space, few studies provide empirical evidence documenting the efficacy of different fuel modification practices under real wildfire conditions. The 2018 Woolsey Fire in Los Angeles County, California, occurred a short time after high-resolution (0.07 m^2) land cover data were created, providing a unique opportunity to quantify vegetation before the fire. We integrated measurements from this high-resolution land cover data with parcel data, building attributes, and environmental context. We then used Random Forests models to analyze the extent to which these factors predicted structure loss in the wildfire. Variable importance scores showed vegetation around buildings was not a strong predictor of building-level damage outcomes compared to building materials and landscape features such as paved land cover per parcel, elevation, building density, and distance to road networks. Among building materials, multi-paned windows and enclosed eaves were most highly associated with building survival. These results are consistent with other studies that conclude building materials and environmental context are more related to survivorship than defensible space.

1. Introduction

Across the globe, there are growing concerns about the size, frequency, and destructiveness of wildfire events (Tedim et al., 2018). For example, Australia (Davey and Sarre, 2020), Chile (Reszka and Fuentes, 2015), and Southern Europe (Molina-Terrén et al., 2019) have all experienced record losses due to wildfire in the past decade. In California, USA, the number of buildings lost in wildfires has also broken records, with more than 40,000 buildings destroyed between 2013 and 2018 (Syphard and Keeley, 2019). These losses reflect the wide-ranging effects of housing growth in the wildland-urban interface (Radeloff et al., 2018), land use change (Syphard et al., 2013), vegetation management legacies in forested and natural areas (Syphard et al., 2019; Hagmann et al., 2021), and climate change, via increased fire activity and altered fire regimes (Iglesias et al., 2022). While these broad-scale factors affect building exposure to wildfire, it is the attributes of the nearby landscape, together with localized characteristics of buildings and vegetation that determine building survival (Quarles et al., 2010; Syphard et al., 2014, 2019).

Landscape attributes such as building position (e.g., slope, aspect, elevation) and proximity to irrigated lands or water bodies can mediate wildfire behavior and ignition, while access to road networks may affect fire spread and suppression access (Syphard et al., 2017; Gibbons et al., 2018; Penman et al., 2019). At smaller scales, building features and vegetation around a building are also thought to play an important role in building survival. During wind-driven events that cause most structure loss (Syphard et al., 2022b), buildings typically experience a shower of wind-blown embers, which can originate from several kilometers away (or more) (Quarles et al., 2010; Hakes et al., 2017; Caton et al., 2017). Embers may directly ignite a building when they accumulate on flammable materials or they may enter vents, windows, or other gaps in the building. When embers land on combustible materials such as dry

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https://doi.org/10.1016/j.jenvman.2023.118960
Received 22 March 2023; Received in revised form 5 September 2023; Accepted 7 September 2023
Available online 30 September 2023
0301-4797/Published by Elsevier Ltd.

vegetation (trees, mulch, leaf litter, etc.) or nearby buildings and attachments (decks, sheds, etc.) they can lead to indirect ignitions; and as surrounding materials begin to burn, they expose the building to direct flame contact and radiant heat (Quarles et al., 2010; Hakes et al., 2017; Caton et al., 2017). Defensible space is meant to reduce the flammability of vegetation near buildings, as well as other features (e.g., decks, propane tanks), to moderate fire behavior, and enhance firefighter safety.

Accordingly, many scientists and managers argue that using fire-resistant materials and ensuring adequate defensible space are key to reducing losses (Quarles et al., 2010; Hakes et al., 2017). However, it remains challenging to determine which attributes of buildings, defensible space, and surrounding vegetation and landscapes, and under which conditions, can best improve the chance of building survival. Research examining post-fire outcomes in relation to these different attributes have become increasingly common (e.g., Syphard and Keeley, 2019; Knapp et al., 2021; Troy et al., 2022).

Such studies have identified enclosed eaves, vent screens, multi-pane windows, and ignition-resistant siding as particularly effective in limiting ember penetration (Syphard and Keeley, 2019; Price et al., 2021; Troy et al., 2022). Other building features like deck and roof materials are also commonly implicated as influencing building survival (Quarles et al., 2010). Requiring these upgraded materials in codes in California have resulted in higher rates of building survival in wildfire (Knapp et al., 2021; Baylis and Boomhower, 2022). However, retrofitting these materials may be costly.

In comparison to changing building materials, creating defensible space may be less expensive, but post-fire assessments have yielded inconsistent conclusions about critical locations or scales at which to implement defensible space. For example, Syphard and Keeley (2019) found building material were stronger predictors of building survival than defensible space in a sample of 40,000 buildings in California. In Northern California, Knapp et al. (2021) found that although vegetation in the 0–30 m defensible space zone did not significantly predict home survival, there was a strong correlation between vegetation cover in the 30–100 m zone and home survival. In Australia, Price et al. (2021) found creation of defensible space (up to 50 m from the home) as well as mid-level forest cover within 10 m were significantly related to outcomes (but not vegetation overhanging the roof, vegetation cover within 10 m of the house and the state of the lawn). Other studies from Australia and California concluded vegetation immediately around the home (e.g., touching or overhanging buildings) was most influential in determining survival, with no significant improvement in survival defensible space exceeded 20–30 m (Penman et al., 2013; Miner, 2014; Syphard et al., 2014).

Inconsistencies in past studies may reflect, in part, variation in measurements of defensible space, with different time periods, data sources, sample sizes, and definitions. The most detailed information comes from studies with smaller sample sizes. For example, Syphard et al. (2014) and Miner et al. (2014) relied on pre-fire aerial imagery to allow manual calculations of defensible space for individual buildings (2000 for Syphard et al. (2014) and n $<$ 500 for Miner (2014)). California has amassed a large dataset from post-fire, on the ground assessments of wildfire losses (Damage Inspection Survey, or "DINS", currently more than 40,000 buildings). Until recently, however, these surveys have focused primarily on building materials, with less information on defensible space (Syphard and Keeley, 2019). However, advances in remote sensing, including LiDAR and resultant high-resolution land cover data are making it increasingly possible to examine defensible space for much larger numbers of buildings (Price et al., 2021).

For this study, we used a high-resolution (0.07 m^2) landcover data set to consider the role of defensible space, relative to building materials and landscape-level attributes, and examine building loss and survival for nearly 11,000 buildings after the 2018 Woolsey Fire in Southern California. Using an 8-class high-resolution land cover dataset derived from LiDAR and aerial imagery (Galvin et al., 2019) we were able to compare different measures of vegetation, including tree cover, shrub, and grasses, and at different scales and locations (e.g., with increasing distance from buildings and trees overhanging buildings). This fire and location were an apt setting for such a study: the Woolsey Fire was a large and intense fire that destroyed 1643 buildings in a range of settings (Los Angeles County, 2019a,b) (Fig. 1); California is unique among U.S. states in requiring fire-resistant materials and defensible space for buildings in designated high-hazard zones (Baylis and Boomhower, 2022); and future wildfire is likely. Examining the relative importance of different attributes of buildings, defensible space, and surrounding landscape can provide insight for future investments at the building and community-level to reduce wildfire risk.

2. Methods

2.1. Study area and Woolsey Fire

The Santa Monica Mountains are an east-west coastal mountain range in Southern California, between the Pacific Ocean and the Los Angeles metropolitan area (Fig. 1). Just over half of the land is publicly owned and protected in the Santa Monica Mountain National Recreation Area (SMMNRA), with the National Park Service coordinating with a range of state, county, and local governments that own land (Syphard et al., 2019). Of the privately owned land in SMMNRA (45% of total), about a quarter has already been developed, ranging from sparsely distributed rural communities to densely populated housing subdivisions on small lots. As a whole, the area is considered wealthy, but has a wide variety of housing age, materials, and neighborhood configurations, particularly in more remote areas (Los Angeles County, 2019a,b).

SMMNRA is notable for its size and biodiversity: it forms the largest expanse of protected Mediterranean-type habitats in the world, with more than 1000 species of plants and 500 vertebrate species (Syphard et al., 2019). The evergreen, sclerophyllous shrubland vegetation association, chaparral, is the most extensive vegetation type, intermixed with sage scrub, oak woodland, riparian woodland, and grasslands. This area is highly fire-prone, with most of the landscape having burned at least once and some up to 14 times since record keeping began in the early 20th century (Levin, 2019). The areas of highest fire frequency occur within canyons that form corridors for wildfire, especially during Santa Ana winds (strong downslope winds that originate inland, often during the fall) (Guzman-Morales et al., 2016).

Given the fire history of the region, there have been decades of efforts to enhance defensible space and building materials. Starting in the 1960s, California began requiring homeowners to maintain defensible space in fire prone areas (initially, the first 9.1 m (30 ft) around a building). That requirement has since expanded to 30.5 m (100 ft), with additional requirements for the ember-resistant zone within 0.3 m (5 ft) of a building starting in 2023 (*Public Resources Code (PRC). Division 4. Part 2. Chapter 3. Mountainous, Forest-, Brush- and Grass-Covered Lands [4291–4299] (1965 and rev. 2021)*). Other jurisdictions can exceed these requirements; for example, Los Angeles County, which covers much of the Santa Monica Mountains, can extend defensible space requirements up to 61 m (200 ft) depending on setting (Los Angeles County, California-Code of Ordinances Title 32-FIRE CODE 4908.1 2019). Building material requirements statewide began with roof materials in the 1990s and were incorporated into Chapter 7A addition of the California Building Code in 2008. Requirements apply to new construction and include roof coverings, windows, vents, exterior walls, and decks (*International Code Council, California Building Code, Part 2, 2016, Chapter 7a. pp. 285–292, vols. 1–2016.*). Retrofits are not required except when a building is being substantially remodeled (including roof replacements).

The Woolsey Fire ignited near the boundary of Ventura and Los Angeles Counties on November 8, 2018 under severe Santa Ana wind conditions. With wind speeds reaching up to 97 km/h (60 mph), the fire crossed the multi-lane 101 Freeway overnight and reached the ocean 6.5 h later, with most of the area burned and buildings lost on November

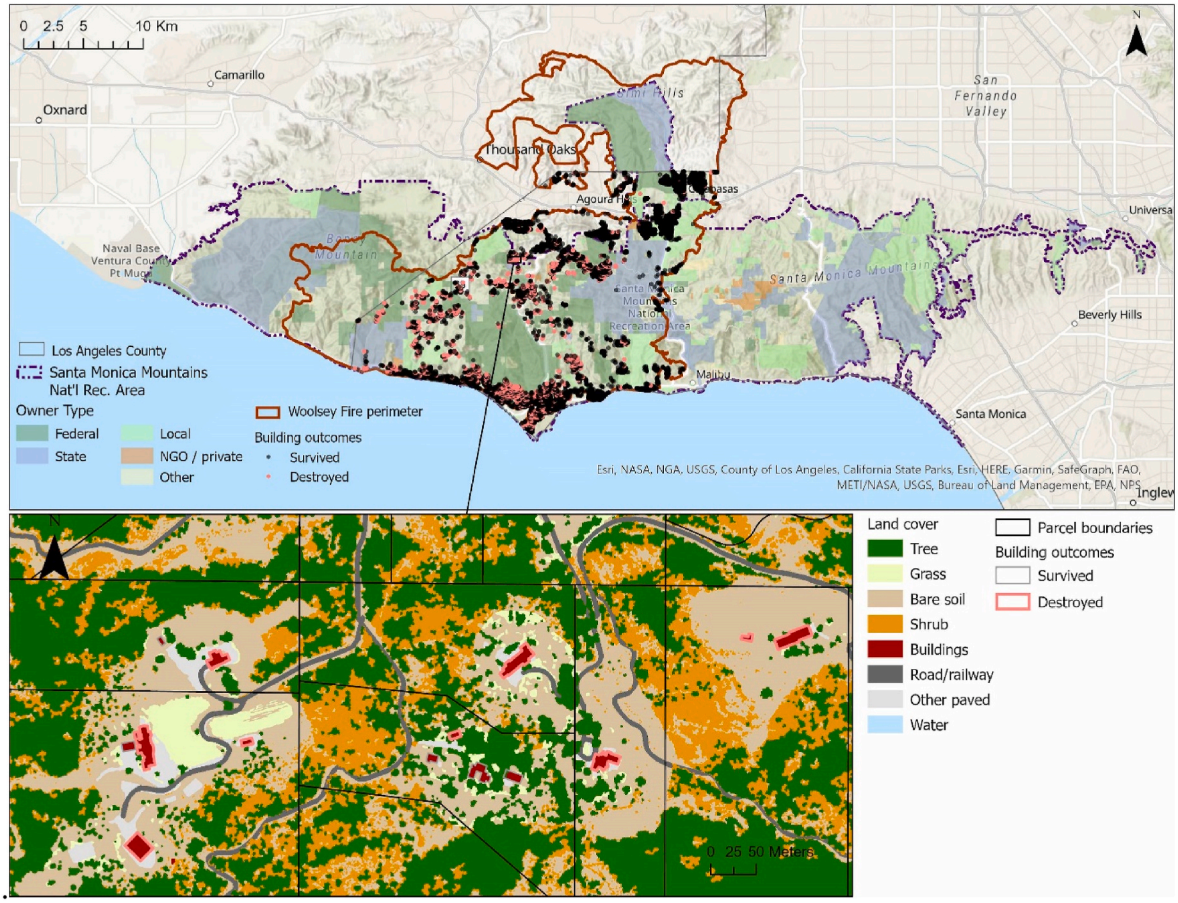

Fig. 1. Study area demonstrating Woolsey Fire perimeter and Santa Monica Mountains National Recreation Area, with buildings destroyed and survived in Los Angeles County with example inset showing eight class land cover (2016), parcel boundaries and building outcomes in Agoura Hills area.

9th. The Woolsey Fire was massive in size, likely due to extensive dieback after a prolonged drought, resulting in rapid fire spread via large-size ember generation, long-distance transport, and high ignition potential (Keeley et al., 2022). Like most Santa Ana wind-driven fires in chaparral-dominated systems, it burned at high intensity with moderate-to high-severity throughout most of the perimeter (Jin et al., 2015; Keeley et al., 2022) (Jin et al., 2015; Keeley et al., 2022). By November 21, 2018, the fire had caused the evacuation of more than 295,000 people, burned 392 km^2 (151 sq mi), led to three fatalities, destroyed 1643 buildings and damaged 364 buildings (totals include Ventura and Los Angeles Counties) (Los Angeles County, 2019a,b) (Fig. 1).

Buildings within the Woolsey perimeter (from parcel data and CAL FIRE's DINS data, described below) were primarily found in areas classified as wildland-urban interface (WUI), areas where housing (density of at least 1 home per 40 acres) is intermingled with or in close proximity to wildland vegetation (Supplemental Table 1) (Radeloff et al., 2022). WUI development can be either "intermix" where housing is intermingled with wildland vegetation or "interface" WUI, housing without substantial wildland vegetation, but found in proximity to a sizeable area of wildland vegetation (USDA and USDI, 2001; Radeloff et al., 2018). Typically interface areas hold more houses, as they are densely developed (Radeloff et al., 2018). Within the Woolsey Fire perimeter, 61.1% of all buildings were in interface areas vs. 27.8% in intermix (total of 88.9% of all buildings in the fire perimeter) (Supplemental Table 1). Non WUI areas can be those that lack substantial wildland vegetation (7.4% of buildings in the Woolsey Fire perimeter), or more rural or remote areas with wildland vegetation that fall below the housing density threshold (3.8%). The majority of buildings destroyed were in interface areas (46.5% of losses), but with losses also found in the intermix (31.9% of losses), and non WUI areas as well (non WUI with vegetation-17.1%, non WUI without vegetation-4.6%) (Supplemental Table 1).

2.2. Land cover and data assembly

We relied upon different data sources, including the high-resolution land cover, parcel data from Los Angeles County, and CAL FIRE's DINS program. Below we describe land cover processing and how we integrated parcel and DINS data to create our sample of destroyed and surviving buildings.

The land cover data were derived from a combination of high-resolution imagery and LiDAR acquired in 2016. Object-based feature extraction techniques that integrated the LiDAR and imagery with publicly available thematic datasets (e.g., roads) were used to map eight land cover following methods detailed in O'Neil-Dunne et al. (2013): (1) tree canopy, (2) grass/shrub, (3) soil (i.e., bare earth), (4) water, (5) buildings, (6) roads, (7) other paved surfaces, and (8) tall shrubs (defined as 0.15–2.43 m in height [0.5–8 ft]). We used the land cover data to summarize vegetation and other land cover near buildings (see more in 2.3 Predictors).

We clipped parcel boundaries from Los Angeles County (Assessor Parcels – 2015 Tax Roll, 2016) to a 100 m buffer around the Woolsey Fire perimeter. As the DINS data confirmed, all destroyed buildings were located within the fire perimeter. We visually inspected unburned building footprints that intersected the wildfire perimeter and retained only those that were within the perimeter (n = 234 out of 317). The 100 m buffer allowed us to avoid edge effects and to ensure we could fully calculate defensible space for buildings near the perimeter. While many fire perimeters contain patches of unburned vegetation, the overall fuel moisture preceding the Woolsey Fire was so low, and the wind so intense, that there were few patches of unburned vegetation within (Keeley et al., 2022). Accordingly, we used all buildings within the fire perimeter for modeling.

CAL FIRE's DINS program collected data on 1712 buildings in Los Angeles County in the aftermath of the Woolsey Fire, focusing on damaged and destroyed buildings. Each building surveyed was classified as Affected [1–9%], Minor [10–25%], Major [26–50%], or Destroyed [>50%]. Following previous studies, we grouped Destroyed or Major Damage together as destroyed, and classified buildings with less than 25% damage as surviving, along with all other unburned buildings within the fire perimeter but not in the DINS dataset (Assessor Parcels – 2015 Tax Roll, 2016; Syphard and Keeley, 2019).

For all buildings in DINS data, we used GIS to match the geographical coordinates of the DINS building locations to the building footprints in our dataset, and verified that parcel identifiers matched between DINS and parcel data. We were able to match 1485 buildings from DINS data to building footprints and identified another 9416 buildings within the fire perimeter. Our final dataset included 10,901 buildings on 6270 parcels, 1302 of which were destroyed in the Woolsey Fire (11.9%) and 9599 of which survived (88.1%).

2.3. Predictors

Considering the range of factors associated with building loss in California (Syphard et al., 2017; Knapp et al., 2021; Troy et al., 2022), and other regions (Penman et al., 2019; Price et al., 2021), we assembled 70 variables in five themes: proximity to other destroyed buildings, which we have termed exposure (1 variable), building construction (10), defensible space (24), landscape attributes (29), and topography (6) (Supplemental Table 2). We discuss each theme in turn, below.

We used eight aspects of building construction available from those buildings surveyed by DINS (n = 1485) (Table 1), discarding one variable about elevated deck/porches, as it contained data for less than 10% of the buildings in DINS. Construction predictors from DINS included: materials used in on grade deck/porches (composite, masonry/concrete, wood, no deck/porch, unknown); eaves (enclosed, unenclosed, no eaves, unknown); exterior siding (combustible, ignition-resistant, unknown); fence materials (combustible, non-combustible, no fence, unknown); carport/covered patio materials (combustible, non-combustible, no patio/carport, unknown); roof materials (asphalt, concrete, metal, tile, wood, other, unknown); vent screen (mesh screen ≤ 3.2 mm [1/8"], mesh screen > 3.2 mm [1/8"], unscreened, no vents, unknown); and window pane (single-pane, multi-pane, no windows, unknown). Although detailed construction material information was only available for the DINS buildings, we had information on building age through "effective year" in parcel data. Effective year is the most recent year in which significant construction occurred, and has been used as a proxy for materials (Syphard et al., 2017; Baylis and Boomhower, 2022), assuming newer buildings are more likely constructed with fire-resilient materials given building code updates and other improvements in structure design. We termed this "year built" and assigned to each building on a parcel.

We considered 24 different measures of defensible space, at different scales, predominately derived from high resolution land cover (Supplemental Table 2). First, we focused on the individual building, determined if trees were overhanging the building roof, creating a binary variable (0/1). For buildings with trees overhanging the building, we measured the percentage of building covered by trees and the average height of trees over buildings (Supplemental Table 2). For each building perimeter, we calculated the nearest distance to shrub, tree, and other buildings (Fig. 1). For each building we then calculated the percentage of land cover (as above, for eight land cover types) for the two areas we considered to be under parcel/building owner and or resident control: 1) the area within 3 m [10 ft] radii around the building footprint and 2) the area in the parcel as a whole. Two final measures of defensible space came from DINS: distance to propane tank (0–3 m [10 ft], 3.1–6.1 m [11–20 ft], 6.2–9.1 m [21–30 ft], >9.1 m [>30 ft], no tank, unknown) and vegetation clearance (0–9 m [30 ft], 9.1–30.5 m [30–100 ft], >30.5 m [>100 ft], not applicable, unknown).

We had 29 attributes characterizing the landscape around buildings, including vegetation and the percentage of land cover classes within 30.5 m [100 ft], 61 m [200 ft], and 91.4 m [300 ft]) radii around the building. We included additional data on infrastructure to assess whether building density or distance to roads mediated the effect of defensible space on building survival. We used GIS to interpolate building density with moving-window search radius of 1-km (Microsoft Building Footprints from 2017) (https://www.microsoft.com/en-us/maps/building-footprints). We also calculated the Euclidean distance to all roads and primary roads based on the 2010 U.S. TIGER line Census data (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html. We also included parcel area as a measure of development intensity and size (Supplemental Table 2).

Following Syphard et al. (2017) we included measures of topography for each building, all derived from a 30 m DEM (https://www.usgs.gov/the-national-map-data-delivery). For elevation, slope, and aspect (0–360°), we calculated mean values for a 30 m and 100 m buffer around the building, to characterize the building position and the area around the building.

2.4. Statistical analyses

2.4.1. Variable selection and individual predictors

To evaluate redundancy of predictor variables, we examined correlations between all continuous predictors. All analyses were performed using R Statistical Software (v4.1.2, R Core Team, 2023). Thirty-five variable pairs had Pearson's correlation coefficients greater than 0.7. This was anticipated since land cover at the parcel level is correlated by design; land cover classes are part of the same whole. Similarly, land cover proportions within buffers of increasing size will be related. In order to reduce potentially redundant predictors, we individually regressed each predictor against building outcome, creating bivariate logistic regression models (Syphard and Keeley, 2019; Price et al., 2021). We calculated deviance explained from each model and among similar variables selected only those with highest deviance explained for multivariate models (e.g. selected only one variable pertaining to tree canopy overhang, one measure of parcel-level land cover, one buffer measure of land cover for each class) (Table 1, Supplemental Table 2). We calculated correlations for remaining predictors and all were below 0.7 except for the percentage of a parcel covered by building and the percentage of building land cover within a 91.4 m (300 ft) buffer (Pearson r = 0.713). Looking at the model fit indices (deviance explained, AIC, AICc, BIC, and R^2) the percent of the parcel covered by building outperformed the 91.4 m (300 ft) buffer variable, so we retained only percent parcel built, retaining a total of 32 variables for further analysis (Table 1).

For each of these final variables retained for analyses, we present deviance explained from bivariate regressions (Table 1). We also tested to see if there were significant differences in variables between surviving and destroyed buildings using the Wilcoxon rank sum tests for continuous variables and Fisher's exact test for categorical variables, and examined differences (in classes for categorial variables, median values for continuous) between building outcomes. We calculated the destruction rate (percent of buildings lost relative to all buildings present) for categorical variables and for key continuous variables, calculating destruction rates by quintiles or other breaks in data. When examining these variables individually it is unclear how variables might reflect correlations with other factors of interest, and/or be mediated by multiple predictors at different scales. To better understand these multivariate relationships we turned to Random Forests analyses.

Table 1
Winnowed predictor variables, along with their theme and results from bivariate models including the percentage of deviance captured in a bivariate logistic regression of building loss, the number of observations for each variable, and source. For categorical variables only (DINS data, construction) we calculated destruction rates for each value. Theme codes are EXP = exposure; CON = construction; DEF = defensible space; LAND = landscape attributes; and TOPO = topography. See Supplemental Fig. 1 for destruction rates for key continuous variables.

Theme	Variable	Description	Overall, N = 10,901[1]	Destroyed, N = 1,302[1]	Survived, N = 9,599[1]	*Destruct-ion rate (categ. data)*	p-value[2]	% Deviance	Source
CON	build_area	Building area (m^2)	213 (97, 333)	222 (120, 322)	212 (93, 335)		0.04	0.06	DINS
CON	build_DECKPORCHO	On-grade deck/porch materials					0.2	0.47	DINS
		Composite	7 (0.7%)	5 (0.6%)	2 (1.1%)	71.4%			
		Masonry/Concrete	379 (40%)	319 (41%)	60 (34%)	84.2%			
		No Deck/Porch	511 (54%)	413 (53%)	98 (56%)	80.8%			
		Wood	54 (5.7%)	40 (5.1%)	14 (8.0%)	74.1%			
		Unknown	9950	525	9425				
CON	build_EAVES	Eaves					<0.001	5.36	DINS
		Enclosed	110 (23%)	51 (16%)	59 (34%)	46.4%			
		No Eaves	190 (39%)	149 (48%)	41 (24%)	78.4%			
		Unenclosed	184 (38%)	111 (36%)	73 (42%)	60.3%			
		Unknown	10,417	991	9426				
CON	build_EXTERIORSI	Exterior siding					0.2	0.16	DINS
		Combustible	298 (27%)	257 (27%)	41 (23%)	86.2%			
		Ignition Resistant	822 (73%)	684 (73%)	138 (77%)	83.2%			
		Unknown	9781	361	9420				
CON	build_FENCEATTAC	Fence materials					0.003	1.12	DINS
		Combustible	79 (7.6%)	58 (6.7%)	21 (12%)	73.4%			
		No Fence	755 (73%)	644 (75%)	111 (63%)	85.3%			
		Non-Combustible	202 (19%)	158 (18%)	44 (25%)	78.2%			
		Unknown	9865	442	9423				
CON	build_PATIOCOVER	Carport/covered patio materials					0.4	0.21	DINS
		Combustible	178 (19%)	147 (19%)	31 (18%)	82.6%			
		No Patio Cover/Carport	655 (69%)	540 (70%)	115 (67%)	82.4%			
		Non Combustible	113 (12%)	87 (11%)	26 (15%)	77.0%			
		Unknown	9955	528	9427				
CON	build_ROOFCONSTR	Roof materials					<0.001	2.17	DINS
		Asphalt	432 (40%)	369 (41%)	63 (36%)	85.4%			
		Concrete	34 (3.2%)	24 (2.7%)	10 (5.8%)	70.6%			
		Metal	218 (20%)	188 (21%)	30 (17%)	86.2%			
		Other	18 (1.7%)	10 (1.1%)	8 (4.6%)	55.6%			
		Tile	347 (33%)	285 (32%)	62 (36%)	82.1%			
		Wood	18 (1.7%)	18 (2.0%)	0 (0%)	100.0%			
		Unknown	9834	408	9426				
CON	build_VENTSCREEN	Vent screen					0.4	0.53	DINS
		Mesh ≤ 3.2 mm (1/8″)	118 (28%)	76 (29%)	42 (27%)	64.4%			
		Mesh >3.2 mm (1/8″)	99 (24%)	66 (25%)	33 (21%)	66.7%			
		No Vents	179 (43%)	110 (42%)	69 (45%)	61.5%			
		Unscreened	21 (5.0%)	10 (3.8%)	11 (7.1%)	47.6%			
		Unknown	10,484	1040	9444				
CON	build_WINDOWPANE	Window pane					<0.001	4.68	DINS
		Multi Pane	249 (44%)	143 (36%)	106 (62%)	57.4%			
		No Windows	75 (13%)	62 (16%)	13 (7.6%)	82.7%			
		Single Pane	245 (43%)	192 (48%)	53 (31%)	78.4%			
		Unknown	10,332	905	9427				
CON	parcel_year_built	Year built	1981 (1970, 1991)	1976 (1964, 1986)	1983 (1971, 1991)		<0.001	0.01	Parcel
		Unknown	1001	111	890				
DEF	build_min_dist_shrub	Dist. to shrub (m)	55 (22, 125)	40 (18, 91)	58 (23, 128)		<0.001	0.5	Land Cover
DEF	build_min_dist_tree	Dist. to tree (m)	0.23 (0.23, 0.23)	0.23 (0.23, 0.23)	0.23 (0.23, 0.23)		<0.001	0.38	Land Cover
DEF	build_near_build	Dist. nearest building (m)	5 (2, 12)	9 (3, 20)	5 (2, 11)		<0.001	0.51	Land Cover
DEF	build_overhang_ht	Av height of trees overhanging building (m)	4.1 (0.0, 6.8)	4.8 (1.6, 7.4)	4.0 (0.0, 6.6)		<0.001	0.56	Land Cover
		Unknown	46	8	38				
DEF	build_PROPANETAN	Distance to propane tank					0.025	1.85	DINS
		1.0 3 m (10 ft)	60 (7.1%)	55 (7.5%)	5 (4.6%)				
		2.3.1–6.1 m (11–20 ft)	59 (7.0%)	56 (7.6%)	3 (2.8%)				
		3.6.2–9.1 m (21–30 ft)	51 (6.0%)	42 (5.7%)	9 (8.3%)				
		4. >9.1 m (>30 ft)	113 (13%)	105 (14%)	8 (7.4%)				
		None	560 (66%)	477 (65%)	83 (77%)				
		Unknown	10,058	567	9491				
DEF	build_VEGCLEARAN	Defensible space-vegetation clearance					0.011	0.96	DINS

(*continued on next page*)

Table 1 (*continued*)

Theme	Variable	Description	Overall, N = 10,901[1]	Destroyed, N = 1,302[1]	Survived, N = 9,599[1]	*Destruct-ion rate (categ. data)*	p-value[2]	% Deviance	Source
		1.0–9.1 m (0–30 ft)	1014 (89%)	888 (90%)	126 (83%)				
		2.9.1–30.5 m (30–100 ft)	103 (9.0%)	79 (8.0%)	24 (16%)				
		3. > 30.5 m (100 ft)	22 (1.9%)	20 (2.0%)	2 (1.3%)				
		Unknown	9762	315	9447				
DEF	parcel_Build_P	Parcel land cover - % buildings	13 (5, 26)	7 (2, 13)	14 (5, 28)		<0.001	6.97	Land Cover
EXP	build_near_dest	Dist. to destroyed building (m)	212 (55, 498)	20 (6, 49)	264 (88, 565)		<0.001	23.22	derived from DINS
LAND	build_Mean_builddens	Building density	1.42 (0.7, 2.3)	0.96 (0.5, 1.71)	1.48 (0.78, 2.3)		<0.001	2.24	Syphard et al. (2017)
		Unknown	73	4	69			1.28	
LAND	build_Mean_distroad	Distance to major road (m)	184 (67, 381)	281 (144, 432)	172 (62, 370)		<0.001	1.28	Syphard et al. (2017)
		Unknown	73	4	69			3.62	
LAND	build_p_grass_300	Percent grass, 91.4 m (300 ft)	14 (9, 19)	11 (6, 15)	15 (9, 20)		<0.001	5.94	Land Cover
LAND	build_p_otherpaved_300	Percent paved, 91.4 m (300 ft)	7.3 (4.1, 10.9)	4.8 (2.3, 7.5)	7.6 (4.4, 11.3)		<0.001	4.18	Land Cover
LAND	build_p_road_300	Percent road, 91.4 m (300 ft)	6.8 (3.4, 11.4)	4.8 (2.6, 7.5)	7.1 (3.6, 11.9)		<0.001	1.19	Land Cover
LAND	build_p_shrub_300	Percent shrub, 91.4 m (300 ft)	0.9 (0.0, 5.6)	2.9 (0.0, 10.2)	0.7 (0.0, 5.1)		<0.001	2.79	Land Cover
LAND	build_p_soil_200	Percent soil, 61 m (200 ft)	19 (9, 34)	29 (18, 40)	18 (8, 33)		<0.001	2.6	Land Cover
LAND	build_p_tree_100	Percent tree, 30.5 m (100 ft)	28 (18, 41)	35 (24, 49)	27 (17, 39)		<0.001	0.07	Land Cover
LAND	build_p_water_100	Percent water, 30.5 m (100 ft)	0 (0,0)	0 (0,0)	0 (0,0)		0.7	0.31	Land Cover
LAND	parcel_area	Parcel area (m^2)	4565 (1,396, 24,752)	7837 (3,358, 39,047)	4288 (1,262, 22,843)		<0.001	0.18	Land Cover
TOPO	build_Mean_aspect_100m_DEM	Aspect, 100 m around build	182 (154, 207)	178 (148, 203)	183 (155, 208)		<0.001	0.06	30 m DEM
TOPO	build_Mean_elev_30m	Elevation, 30 m around build (m)	242 (80, 284)	243 (78, 315)	242 (81, 281)		<0.001	3.59	30 m DEM
TOPO	build_Mean_slope_30m_DEM	Slope (%) 30 m around build	9.0 (5.6, 13.6)	12.0 (7.9, 16.6)	8.6 (5.3, 13.1)		<0.001	6.97	30 m DEM

[1] Median (IQR); n (%).
[2] Wilcoxon rank sum test; Fisher's Exact Test for Count Data with simulated p-value(based on 2000 replicates); Fisher's Exact Test for Count Data.

2.4.2. *Random forest models*

To evaluate the relative importance of predictors in a multivariate context, we used the Random Forest modeling approach with cforest function in the 'party' package in R software, and calculated variable importance scores with the vi function in the 'vip' package (Hothorn et al., 2006; Strobl et al., 2007, 2008; Greenwell and Boehmke, 2020). As an ensemble learning technique, Random Forest builds hundreds of partial regression trees, and then combines them into a robust prediction model. Here, regression tree means an iterative portioning process that groups data into smaller branches in an effort to classify. Random Forest models are therefore apt for datasets that have missing data or non-linear and interacting relationships between variables, such as studies of wildfire building loss (Price et al., 2021). Following Price et al. (2021) we included distance to destroyed building in our Random Forests to account for spatially clustered losses and survival.

Because we had detailed data on construction materials from DINS data for only some data, we created two Random Forest models, both predicting if buildings were destroyed or survived. We first created a Random Forest model with all 10,901 observations, but no DINS variables (22 variables) (hereafter, RF-no DINS) (Table 1). We then ran Random Forest for only those buildings within the DINS dataset (hereafter, RF-DINS), with a total of 1485 observations and all 32 predictor variables. Following Price et al. (2021) we built 500 trees for each Random Forest, and for each Random Forest assessed 'out-of-bag' accuracy (the prediction error for each tree), and examined variable importance (mean loss of accuracy) for the top 20 variables. Given the clustered nature of wildfire exposure and losses, we tested the residuals of the Random Forest models for spatial autocorrelation using a variogram (Ribeiro et al., 2022, Pinheiro et al. 2023). We then created individual conditional expectation (ICE)/partial dependence plots (PDP) for the most important predictors using partial in the 'pdp' package (Greenwell, 2017). The ICE curve is the prediction of the outcome (destroyed or not) for a given value of the predictor, while taking into account the other predictors from a single regression tree in the ensemble. A PDP is the average of the lines of an ICE plot (i.e., ICE plots show one line per observation vs. PDP shows one line). We created PDP plots for the top predictors as the mean and 95% confidence interval of the ICE from the random forest models. To facilitate visualization ICE/PDP curves were centered on the minimum of each predictor value; for each variable the ICE/PDP figures show probability of destruction relative to the minimum value of a given predictor. Negative values therefore indicate a lower probability of loss, while positive values indicate a greater probability of loss relative to the minimum value of that predictor. For categorical predictors, a single reference category was chosen (e.g., multi-pane for windows).

3. Results

3.1. *Individual variables*

Distance to the nearest destroyed building had by far the greatest deviance captured in the bivariate models (23%) (Table 1). Median distance to a destroyed building was 20 m (66 ft) for buildings lost vs. greater than 264 m (865 ft) for buildings that survived (Table 1, Supplemental Fig. 1). Another five predictors had more than 4% of deviance explained, including two characteristics of construction (eaves, windows), and several measures of the built environment (percent of parcel with buildings, percent paved and percent covered by roads in 91.4 m buffer around buildings) (Table 1).

We then examined each individual variable, grouped by theme (Table 1). Among construction, six variables were statistically significantly related to building outcome. Buildings destroyed were larger and older than those surviving, although differences in median values were small. Among materials, nearly half of destroyed buildings had single pane windows, and buildings with no windows were twice as common in buildings destroyed than those surviving (Table 1). Conversely, multi-pane windows were twice as common in surviving than destroyed buildings. Buildings with no eaves made up nearly half of all destroyed buildings, and were twice as common in destroyed than surviving buildings) (Table 1). Enclosed eaves were less prevalent in destroyed buildings (half the proportion found for surviving buildings). Unenclosed eaves were also slightly less common in destroyed buildings (36% destroyed vs. 42% surviving). Fence and roof materials were also statistically significantly related to building outcomes, although there were few notable differences in materials between destroyed and surviving buildings (Table 1). For example, among popular roof materials, asphalt was more common among destroyed buildings, with tile slightly more common among surviving buildings (Table 1). Unexpectedly, metal roofs were slightly more prevalent among destroyed buildings (Table 1). For fences, only 26% of the approximately 1000 buildings had fences of any kind, and both combustible and noncombustible fences were more prevalent in surviving buildings.

Only one measure of defensible space, percent of parcel with buildings, had more than 4% deviance explained. Buildings lost had a median of 7% built land cover per parcel, half the median 14% for those surviving (Table 1). Although they did not explain substantial deviance in a bivariate model, all other measures of defensible space in our final set of variables were consistently statistically related to building loss (Table 1). Buildings were more likely to be destroyed when they were in closer proximity to trees, shrubs, and other buildings, and when those trees over buildings were taller (Table 1). The defensible space as assessed by DINS also was statistically significantly related to building loss: buildings with the smallest distance class for defensible space (0–9.1 m [0–30 ft]) made up 90% of destroyed buildings, but 83% of surviving buildings, and buildings destroyed were more likely to have propane tanks in close proximity (<6.1 m [20 ft]) (Table 1). Regardless of outcome, all buildings in our study were generally close to vegetation, especially trees (median distance of less than a foot) (Table 1).

All but one of the measures of land cover in our final set of variables were statistically significantly related to building outcomes (water around buildings was uncommon, and not significantly related to building loss). Among landscape features, destroyed buildings were in lower density settings, on larger parcels, farther from major roads, and had more vegetation and less road and paved cover in buffers around buildings (Table 1, Supplemental Fig. 1). Surprisingly, soil land cover was more common around destroyed buildings than surviving, with median of 29% vs. 18% in the 61 m (200 ft) buffer (Table 1), perhaps reflecting the challenge of differentiating bare soil from dead herbaceous vegetation. All topography variables included in our final set of variables were consistently statistically related to building loss, with expected relationships—buildings destroyed were at higher elevations, on steeper slopes, with southern aspect (Table 1, Supplemental Fig. 1). However, median values between destroyed and surviving buildings were similar, and variables did not explain substantial deviance (Table 1).

3.2. Random forests

The variogram of random forest model residuals were free from spatial autocorrelation. The RF-no DINS model had 95.8% accuracy with 4.1% false negative and 0.1% false positive rates on the complete dataset. This model identified distance to destroyed building (exposure) as the best predictor of building destruction by far. Building area and percent of parcel covered with built land cover were 2nd and 3rd most influential variables, but with far smaller importance scores, followed mostly by landscape and topography variables (Fig. 2).

We further examined the relationship between variables and outcomes through the PDP plots (Fig. 2). The best predictor in the RF-no DINS model, distance to destroyed building, had a strong negative association with building loss at short distances. After ~300 m (~1000 ft), greater distance to destroyed buildings was associated with gradually declining probabilities of loss. The area of the building, alternatively, was negatively associated with destruction until 490 m (~5300 ft^2) where it became a positive predictor of loss; buildings over 490 m (5300 ft^2) had a positive and increasing risk of loss when building size was larger. ICE plots for the remaining seven variables we examined all showed some variation of a "U" shape where prediction of loss first declined from low values of that variable (i.e., survival is more likely) and then increased after some medium value (loss becomes more likely). For example, percentage of parcel built, percent of a 91 m (300 ft) buffer paved, and building density all showed prediction of loss declined until moderate proportions (e.g., ~25% parcel built, ~15% buffer paved) after which prediction of loss increased gradually. Distance to major road and elevation (30 m around buildings) had more variable curves, but similar U shapes. Two measures of vegetation (grass, tree) in buffers were included in these top nine variables mapped with ICE plots. Prediction of loss declined as proportion of grass within 91 m (300 ft) buffer went from 0 to 20%, and then remained stable at higher proportions. Percent tree within 30.5 m (100 ft) of the building showed a U-shaped curve, with declining predictions of loss from 0 to ~20% tree cover, and then rapidly rising predictions of loss to ~40% tree cover, at which point predictions of loss increased only moderately with greater tree cover.

The RF-DINS model had 90.8% accuracy with no false negatives and a 9.2% false positive rate. The most important variables were both measures of materials: window panes and eaves, followed by percent of 91 m (300 ft) buffer paved and distance to destroyed building (Fig. 3). Other variables had variable importance scores of 25 or less, including several other attributes of buildings and two measures of defensible space (percent of parcel built, distance to shrub). The remaining variables selected in the variable importance plots were measures of topography (elevation, aspect, slope) and landscape (distance to major road, building density).

PDP plots revealed that, relative to multi-pane windows, buildings with no windows and single-pane windows had a higher probability of loss. Similarly, buildings with no eaves or unenclosed eaves had higher probability of loss than buildings with enclosed eaves, although the change in probability of loss for these improved materials was smaller than for multi-pane windows in comparison to other window categories. The likelihood of building loss declined sharply as paved land cover in the area 91 m (300 ft) around the building went from 0 to ~10%, beyond which the likelihood of loss was fairly stable. Distance from burned building had a strong negative association, with building loss most likely at short distances from burned building. Vent screen materials had an unexpected relationship, with the lowest probability of loss for unscreened vents—all other categories (no vents, both mesh sizes) had more similar and higher probabilities of loss. These unscreened vents made up only 5% (n = 21) of the observations for which vent materials were present in DINS (Table 1). Distance to major road showed an upside-down U-shaped relationship, with rapidly increasing likelihood of loss as distance went up to 305 m (1000 ft) and then a declining likelihood of loss as distance went out to 914 m (3000 ft).

4. Discussion

As wildfire losses increase across the globe and California, there is a growing urgency to identify mitigation measures that can most effectively protect buildings. Despite detailed pre-fire information on vegetation around nearly 11,000 buildings, we did not find a critical role for

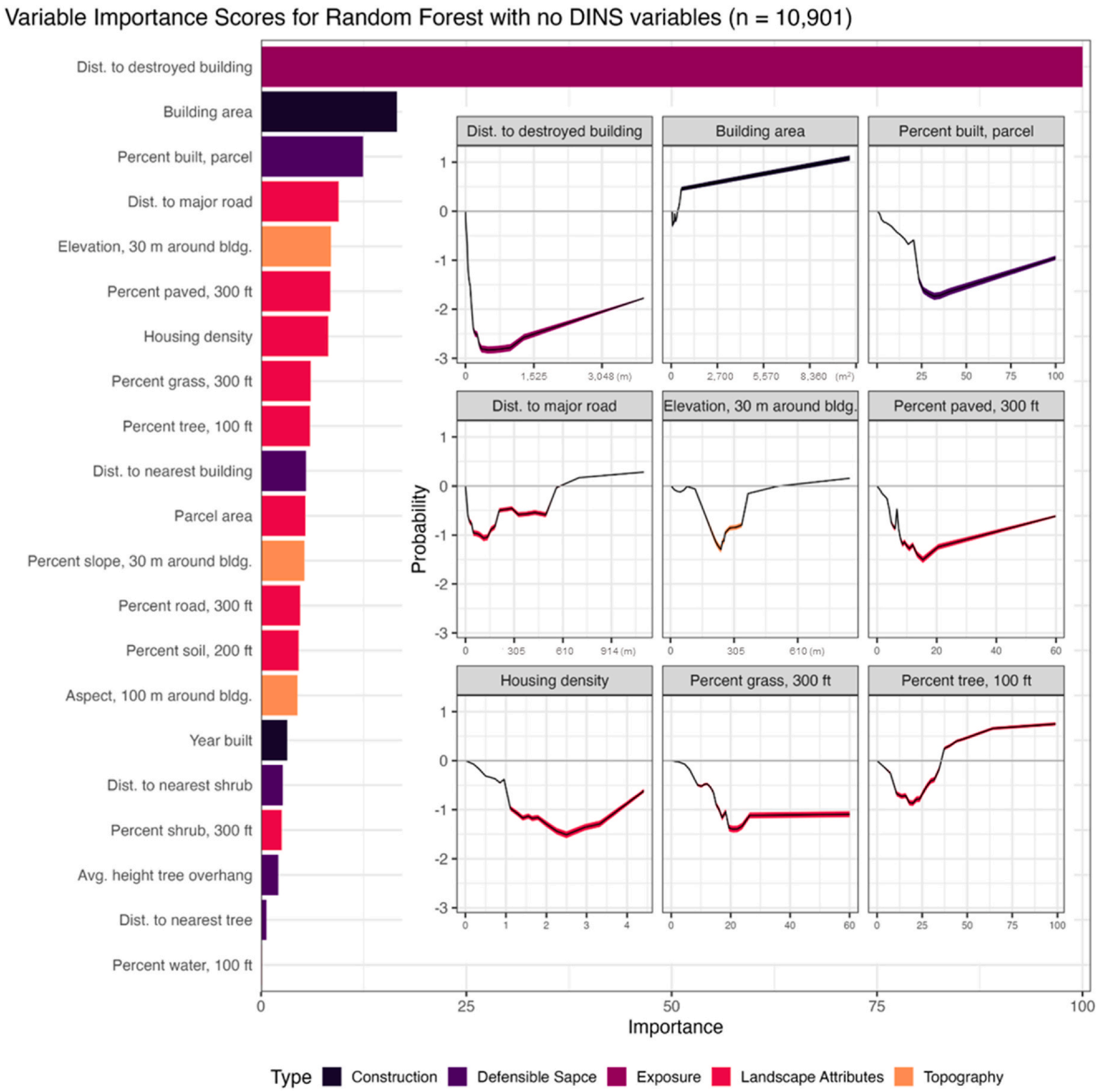

Fig. 2. Random Forest – no DINS. Figure comprising the importance scores for the 20 best variables (scale is the loss of accuracy when each variable is droped from the model) and (inset) the individual conditional expectation plots/partial dependence plots showing probability of loss for the nine most important variables.

vegetation in defensible space in relation to building outcomes after the Woolsey Fire. Instead, building materials and landscape attributes were higher-ranking in variable importance. Below we discuss the attributes of buildings and landscapes we investigated, in turn, along with considerations for mitigation. We conclude with some thoughts about study limitations and future research.

4.1. Proximity to destroyed building

Among all variables and model combinations we considered, proximity to other destroyed buildings was the most highly related variable in relation to wildfire losses. It was the top-ranking factor in the RF-no DINS model, the fourth most important predictor in the RF-DINS model, and it explained the highest level of deviance when considered in a bivariate model. Such proximity to other losses and burning buildings agrees with previous post-fire assessments (Price et al., 2021; Knapp et al., 2021) and corresponds with our understanding of fire spread during wildfires. A burning building creates embers and is a substantial source of radiant heat (Caton et al., 2017). There were likely other factors leading to the strong spatial clustering of wildfire losses, such as similarities in weather and fire conditions, and presence or absence of fire suppression (Price et al., 2021).

When distance from destroyed or burning building is highly influential in post-fire assessments it may indicate that house-to-house fire spread occurred. For example, Knapp et al. (2021) overviewed post-fire assessments and found home-to-home spread was primarily observed in cases where spacing between buildings was less than 10 m (33 ft), although in the 2018 Camp Fire, being less than 18 m (60 ft) to a burning building was associated with higher loss. Such house-to-house spread can result in substantial losses (e.g., the 2017 Tubbs Fire destroyed 76% of buildings within the fire perimeter, many in dense urban areas) (Kramer et al., 2019).

In our study area, although buildings were a median of 4.9 m (16 ft) from other buildings, destroyed buildings were a median of 20 m (65) feet from the nearest burning building (and, a median of 9 m [30 ft] from the nearest building). That is, destroyed buildings overall were most likely to be in lower-density building areas (where houses are further from each other, further from suppression, and there is more wildland vegetation), consistent with other studies (Syphard et al., 2012; Kramer et al., 2018). We note as well that only 11% of the buildings within our

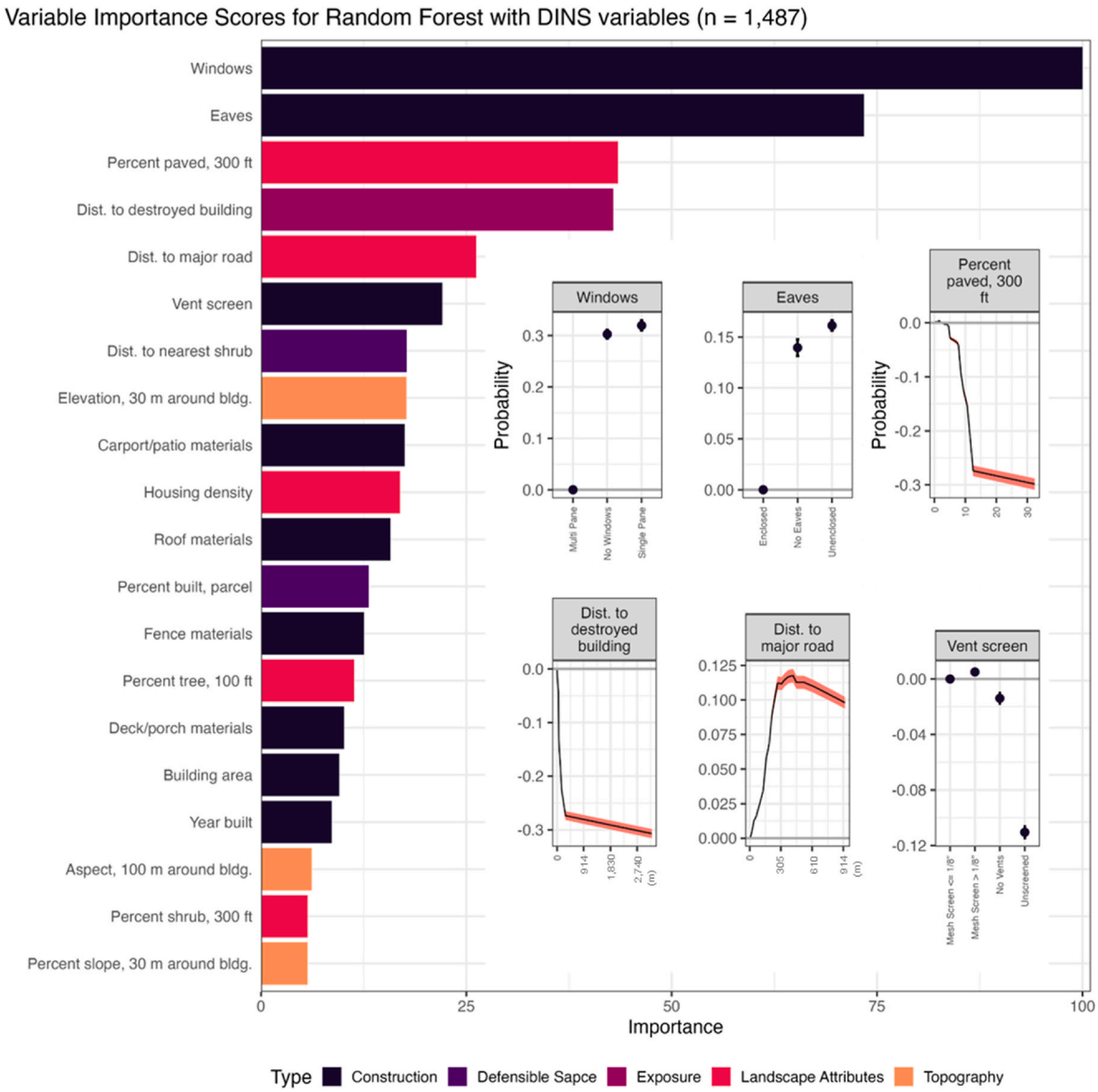

Fig. 3. Random Forest –with DINS. Figure comprising the importance scores for the 20 best variables (scale is the loss of accuracy when each variable is droped from the model) and (inset) the individual conditional expectation plots/partial dependence plots showing probability of loss for the six most important variables.

sample were destroyed (Supplemental Table 1), and destruction rates were highest for the relatively small number of buildings within the lowest density housing (non WUI with vegetation, Supplemental Table 1).

4.2. Building materials and attributes

Among building materials, windows and eaves—specifically multi-pane windows and enclosed eaves—were associated with building survival: the multivariate model (RF-DINS) selected windows and eaves as the top-ranking variables. These variables, and the relative importance of the classes within them, have consistently been identified as critical, including after the Camp Fire in Paradise in 2018 (Troy et al., 2022) and wildfire losses across the state, 2013–2018 (Syphard and Keeley, 2019). Multi-pane windows and enclosed eaves both reduce the likelihood of ember penetration, and multi-pane windows also help withstand radiant heat.

In our dataset, having no eaves and no windows was associated with a higher probability of damage in comparison to enclosed eaves and multi-pane windows. Buildings with no eaves and no windows tended to be small and labelled as miscellaneous structures in DINS data. Such ancillary buildings may have had other factors that led to higher rates of loss, e.g., may have not been priorities for defensive space or other mitigation by homeowners or for defensive actions of firefighters.

Among other building materials, vent screening was the next most important building material in the Random Forest model with DINS data. Mesh screens of both sizes had similar probabilities of loss on the PDP/ICE plots, with slightly lower likelihood of loss when there were no vents; but then there was a larger declining probability of loss when vents were unscreened. The importance of vent screens is well-established in guidelines for homeowner mitigation for wildfire (e.g., https://ucanr.edu/sites/Wildfire/Vents/), and the argument is that the presence of fine mesh screens helps to prevent ember entry. Although our results were consistent with other studies showing finer mesh screens provided more protection than coarser mesh screens, it is unclear why we observed lower loss probability with unscreened vents. Troy et al. (2022) similarly found mesh-covered vents were not statistically significant in reducing risk of loss in a study based on DINS data (while Syphard et al. (2019) found the opposite). Observers may have had challenges discerning materials after buildings were destroyed.

Another possibility for this unintuitive result in this study is that the sample size for buildings with unscreened vents was very low (5% of DINS buildings; half of which survived). With so few samples, this result may relate to some other unobserved attribute of these buildings (e.g., defensive actions).

Several other materials, including roof, fence, and carport/covered patio materials, were less important in predicting building loss in the multivariate models, and examining prevalence among different categories showed limited differences between materials and/or some unexpected results (i.e., combustible and noncombustible fence materials similarly common among destroyed and surviving buildings; metal roofs more common among destroyed than surviving buildings). This agrees with other studies that have found that factors related to potential ember entry tended to be more important than other fire-prone building materials, such as roofs and siding (Syphard and Keeley, 2019). Ember cast is particularly important during wind-driven wildfires because high wind speeds can transport millions of wind-borne embers up to a few kilometers ahead of the fire front (Fernandez-Pello, 2017).

This study, and others, which find a clear benefit to upgraded materials, specifically windows and eaves, support the importance of upgrading building codes and retrofitting older buildings (Baylis and Boomhower, 2022). However, except for roof replacements, retrofits are rarely required or implemented. A different study using DINS data demonstrated that adoption of higher standards for pre-1990 buildings ranged from just over 50% for windows to less than 30% for eaves (Baylis and Boomhower, 2022). The costs to conduct retrofits are not easily standardized across buildings and locations, but can easily run into tens of thousands (Baylis and Boomhower, 2022, Headwaters Economics, and Insurance Institute for Business and Home Safety, 2022).

In our own study, because information about materials was only available for a subset of buildings that were part of the DINS effort, we also included year built from parcel data. However, year built had low deviance explained in a bivariate model and low variable importance score in Random Forest models. These findings differ from other findings on survival and age in California (Syphard et al., 2014; Knapp et al., 2021; Baylis and Boomhower, 2022). It is unclear why; we were assigning year built to all buildings on the parcel which may have obfuscated differences in building types and ages, and we were also considering it as a continuous variable, not looking at the difference in outcomes with classes. Finally, year built may not reflect smaller retrofits – although such improvements are costly this region has some wealthy homeowners.

4.3. Landscape, topography, and defensible space

Important landscape and topography variables from Random Forests models consistently included measures of built and paved land cover (on the parcel, 91 m [300 ft] around a building), as well mean distance to road, mean building distance, and elevation. In contrast, vegetation characteristics at the landscape level or within defensible space were not among the most important variables in Random Forest models. ICE plots for many of these variables showed some variation a “U” shape where prediction of loss first declined from low values of that variable (i.e., survival is more likely) and then increased after some medium value (loss becomes more likely), reflecting the complex relationships with development intensities and wildfire loss, and the variety of settings where buildings were lost in the Woolsey Fire (from densely built lower elevations along the coast to more dispersed buildings at higher elevations).

Our findings about the built environment (roads, building density, paved areas) are similar to other studies showing density and pattern of the built environment were key predictors of loss (Price and Bradstock, 2014; Syphard et al., 2014, 2021). These findings likely reflect a number of mechanisms. For example, we found that building loss exhibited a non-linear relationship relative to the distance to a major road. This may reflect the dual effects that roads may play in the spatial pattern of wildfire, and hence building destruction. For example, while fire ignitions tend to be most frequent close to roads, fires tend to get larger in more remote areas (Syphard et al., 2019). Remote areas are also more challenging for firefighters to access. On the other hand, areas with large amounts of built and paved land cover will be less flammable, and more likely to be in populated areas with better access to firefighting resources. In our study area, rural areas tend to occur at higher elevations with more rugged terrain, which may lead to more erratic fire behavior. Among measures of topography, elevation was ranked higher than slope and aspect on our Random Forest models variable importance. Destroyed buildings had significantly greater elevation than survived buildings in un-adjusted analyses (Table 1). The random forests model showed a “U” shaped relationship between the probability of loss and elevation, with the lowest probability between ~200 m and ~350 m in elevation, and the greatest probability of loss above ~350 m (Fig. 2). Elevation also tends to be associated with other built environment factors, for example, because housing is more easily constructed in low-elevation areas, and is also correlated with factors such as climate and soil moisture that affect vegetation composition and condition.

For defensible space, variables quantifying vegetation surrounding buildings were either not selected as final variables for modeling (e.g., no measures of vegetation 3 m [10 ft] around a building in winnowed variables) or were not strong predictors of building loss in our Random Forest models (e.g., minimum distances to shrub, tree, and tree height overhanging buildings). Modeling outcomes may also reflect the fact that the defensible space was limited for most buildings: 71% of all buildings in our study had trees overhanging the building, and even those buildings without vegetation overhanging the roof were a median of 0.61 m (2 ft) or less from tree cover. Some measures of vegetation were in the top 10 most important variables for Random Forests models (distance to nearest shrub for RF DINS, and grass within 300 ft and tree within 100 ft for RF-no DINS) but with lower importance than built environment. These results are consistent with other studies finding that vegetation characteristics across a broader landscape were more strongly related to burn damage than those in the immediate vicinity of buildings in determining wildfire loss (Knapp et al., 2021; Troy et al., 2022; Meldrum et al., 2022). For example, statewide, landscape-level vegetation was a better predictor of building loss than vegetation at the granular scale of defensible space (Syphard et al., 2021). These findings are of particular interest for the highly biodiverse native vegetation found in Southern California, where removing vegetation might negatively impact ecosystem services (Syphard et al., 2016, 2019), and create demand for irrigation of non-native species.

Finally, our land cover data highlight the challenges of ensuring defensible space—more than 70% of all buildings had tree cover overhanging roofs–even in an area with a long wildfire history and regulations. The Woolsey Fire after action report also noted a need for more public participation in defensible space maintenance, and the challenges of funding inspection and enforcement (Los Angeles County, 2019a,b). Given the challenges of defensible space compliance, and studies concluding that materials are plausibly more influential in determining buildings outcomes, and the other sustainability goals that can be furthered through enhanced materials, it raises questions about the risk reduction benefits that can or will be achieved with a focus on defensible space vs. materials.

4.4. Limitations and additional considerations

Although our study was able to draw a large amount of high-resolution vegetation data for nearly 11,000 buildings, vegetation was nevertheless collected at one point in time pre-fire and summarized to characterize defensible space. For wildland vegetation, there would likely be negligible difference between the date of imagery and the date of the fire. Fuel moisture is typically at its lowest in the autumn in Southern California, due to six months of summer drought in the

Mediterranean climate; and much of the vegetation had experienced dieback from prior drought (Keeley et al., 2022). Nevertheless, irrigation of properties after image dates may have created slight differences in the differentiation of bare soil and grass—e.g., if drought or water restrictions meant grass or other vegetation was dead. Our findings about soil land cover (more common around destroyed buildings than surviving) also likely reflect the challenges of differentiating bare soil from dead herbaceous vegetation.

We prioritized measures of vegetation at different spatial scales (e.g., coverage within different buffers around a building), as opposed to clumpiness of individual trees or green vegetation, or detailed measures of management, factors that can influence building loss (Gibbons et al., 2018). We also were not able to further examine species composition, which may be important because not all tree cover in proximity to buildings present the same wildfire risk. For example, coast live oak (*Quercus agrifolia*) is the dominant oak species here, which like other Southern California oaks, is particularly fire resistant owing to its thick, sclerophyllous, evergreen leaves. Finally, although we considered several buffer distances around buildings, the largest we examined was 91.4 m (300 ft) around a building but considering vegetation at larger distances from buildings might supply additional information (e.g., Syphard et al., 2021).

Our modeling effort reflects the data available to us and assumed every building within the fire perimeter had some exposure to wildfire. We do not have access to detailed information about wildfire exposure and transmission on the ground, although such detailed information has been reconstructed for other fires in intensive case studies (Maranghides et al., 2021). Data collection for DINS is rapidly expanding: more recent assessments have included more undamaged buildings, so that there is now more information on materials for surviving buildings, and information on defensive action taken by firefighters has also expanded. Such defensive action, by homeowners (Price et al., 2021) or firefighters (McNamara et al., 2020) is often critical to building survival—e.g., Price et al. (2021) found house defense was most important variable in a multivariate model, with defended homes three times more likely to survive. The Woolsey Fire, however, burned with exceptional speed, from the mountains down to the ocean in 6.5 h, across a wide swath of the landscape, which meant most of the buildings were lost during a short period when there were limited firefighting resources for defense (Los Angeles County, 2019a,b).

Finally, findings and the building codes present in the study area reflect the conditions that were present in 2018 in the Santa Monica area. Vegetation in this region is changing with type conversion of chaparral to exotic grasses (Syphard et al., 2022a) and temporary dieback of vegetation due to prolonged droughts (Keeley et al., 2022). Continuing to study the changing vegetation conditions, updated building codes and mitigation investments (Miller et al., 2022), as well as post-Woolsey Fire rebuilding will all be necessary to consider future wildfire risk and resiliency.

5. Conclusion

This study joins the emerging body of research examining the relative importance of different attributes of buildings, defensible space, and surrounding vegetation and landscapes on building losses due to wildfire. We used a uniquely detailed land cover dataset to assess defensible space for nearly 11,000 buildings after a major wildfire, and found—similar to other studies—that building materials and landscape attributes were more closely related to wildfire losses than vegetation nearby buildings. While position on the landscape is not easily changed, building materials can be improved over time, and this study joins similar studies in suggesting that investments to reduce ember penetration (e.g., multi-pane windows and enclosed eaves) could be worthwhile contributions to wildfire risk reduction.

Credit author statement

Data curation: M.H.M., D.H.L. and J.O.D.; Formal analysis: M.H.M. and D.H.L.; Investigation & Methodology: M.H.M., D.H.L. and A.D.S.; Project administration: M.H.M.; Software: D.H.L. and J.O.D.; Validation: D.H.L. and J.O.D.; Visualization: M.H.M. and D.H.L.; Lead writing – original draft: M.H.M.; Writing - review & editing: M.H.M., D.H.L., A.D. S. and J.O.D.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Socio-Environmental Synthesis Center (SESYNC) under funding received from the National Science Foundation DBI-1639145. We thank National Oceanic and Atmospheric Administration (NOAA) and the National Fish and Wildlife Foundation (NFWF) for partially funding this study as part of a larger project (No. 0318.19.066989) awarded to the Conservation Biology Institute. Owen Price (University of Wollongong) provided guidance on our initial study design and Todd Hawbaker (USGS) provided thoughtful feedback on a previous version of the manuscript. The findings and conclusions in this paper are those of the author(s) and should not be construed to represent any official USDA or U.S. Government determination or policy.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.118960.

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