

Article

Multiple-Scale Relationships between Vegetation, the Wildland–Urban Interface, and Structure Loss to Wildfire in California

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Abstract: Recent increases in destructive wildfires are driving a need for empirical research documenting factors that contribute to structure loss. Existing studies show that fire risk is complex and varies geographically, and the role of vegetation has been especially difficult to quantify. Here, we evaluated the relative importance of vegetation cover at local (measured through the Normalized Difference Vegetation Index) and landscape (as measured through the Wildland–Urban Interface) scales in explaining structure loss from 2013 to 2018 in California—statewide and divided across three regions. Generally, the pattern of housing relative to vegetation better explained structure loss than local-scale vegetation amount, but the results varied regionally. This is likely because exposure to fire is a necessary first condition for structure survival, and sensitivity is only relevant once the fire reaches there. The relative importance of other factors such as long-term climatic variability, distance to powerlines, and elevation also varied among regions. These suggest that effective fire risk reduction strategies may need to account for multiple factors at multiple scales. The geographical variability in results also reinforces the notion that “one size does not fit all”. Local-scale empirical research on specific vegetation characteristics relative to structure loss is needed to inform the most effective customized plan.

Keywords: fire risk; intermix; interface; vegetation pattern; scale; fire; fuel; housing density; land use; land cover; defensible space



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1. Introduction

In the last three out of four years, California has experienced record-setting wildfires that have cumulatively added up to more than 50,000 structures destroyed. Although California is arguably a worldwide leader in these types of catastrophic events, large-scale human impacts from wildfires are also occurring more frequently in fire-prone ecosystems across the world [1–3] with the 2019–2020 bushfire season in Australia being of notable impact. As losses accrue, the urgency of understanding the factors influencing structure loss is growing. Hence, scientific study of structure loss in wildfire—and why it occurs—is starting to mature. One of the most important overall conclusions resulting from this research is that structure loss is a complex function of multiple interacting factors that vary geographically [4–6], and that much more work is needed to parse out the relative importance of different factors at different scales.

One of the factors that has been difficult to quantify empirically is the role of vegetation surrounding structures and in surrounding landscapes. Defensible space—the reduction of woody vegetation within a buffer surrounding the structure—is widely advocated for its potential to minimize structure loss. Although few studies have been conducted to evaluate its role empirically, its beneficial effects on reducing fire risk have been demonstrated via

simulation or theoretical modeling studies, field experiments, and case studies of individual fire events [7–11].

Two empirical studies in Southern California found a significant benefit of the State-mandated 100' defensible space guideline in reducing house losses [12,13]. In both studies, the most significant effect was observed for vegetation reduction approximately 5–20 m from a structure, after which the protective effect of fuel treatments farther away was not evident. A remote sensing study in Colorado and an analysis of structures lost in 27 fires in Australia also found the most protective benefit of reduced vegetation was in the area immediately surrounding structures [14,15]. In a coarser-scale analysis in Australia, defensible space closest to the structure (i.e., within the first 40 m) was significantly more important than vegetation cover at farther distances [16]. However, vegetation arrangement and fuel moisture could provide the same protective benefit as removing trees and shrubs 40 m around the structure [17].

Although these modeling and empirical studies collectively suggest that reducing vegetation cover close to the structure can minimize the potential for structure loss, broad conclusions remain difficult to assess because the studies were conducted at different scales of analysis using different measurements and were restricted to the unique geographies of the study regions. In addition, the relative importance of defensible space compared to other factors remains unclear, although some studies suggest its relative importance varies based on location, housing pattern, structural characteristics, and scale [11,12,18].

In a statewide and regional-scale analysis using building inspectors' data, Syphard and Keeley [18] found evidence to suggest that structural characteristics were more significantly associated with structure survival than defensible space. In that work, however, defensible space distance may have been unreliably assessed because of the uncertainty in quantifying vegetation in a post fire environment. It is also possible that both surviving and destroyed homes had the same amount of defensible space, so it did not come out as a significant factor. In Southern California, Syphard et al. [12] found that housing arrangement and pattern were more influential than defensible space for explaining structure loss. This result is consistent with other studies that have more broadly revealed housing pattern and topographic variables to be more influential in explaining structure loss than vegetation amount and configuration [6,19] or other proxies for vegetation [4].

An important consideration when examining the factors associated with structure loss in wildfires is that vulnerability to a hazard is a combination of both exposure and sensitivity to the hazard [20]. Exposure means that the geographical location of an asset at risk (e.g., housing pattern and location) can predict its chance of encountering a hazard to begin with; and sensitivity means that, once the hazard is present, the potential for damage is related to local-scale, intrinsic characteristics (e.g., defensible space and structural characteristics). Given that most structures are lost to either direct ember attack, or to the ignition of surrounding elements from ember attack [21], both defensible space and structural characteristics minimize sensitivity by either preventing ember entry to the structure or reducing the flammability of whatever an ember lands upon. Thus, risk of structure loss to wildfires operates at different scales and the role of vegetation may also operate at different scales.

One of the most widely recognized indicators of exposure to wildfire is the wildland–urban interface (WUI [22,23]), which is where human communities are close to natural wildlands. Recent work has confirmed expectations that structure loss is significantly higher in the WUI than in non-WUI areas [24,25]. Although the definition and spatial delineation of the WUI varies widely [26], and may even explicitly account for wildfire probability [27], the most widely used definition and mapping rules are based on the US Federal Register, with two distinct types of WUI defined along with other map classes for varying degrees of development density and vegetation [22,23]. The difference between the two WUI types is the relative housing density and percentage cover of wildland vegetation.

The relationship between the WUI and structure loss is an example of how vegetation can influence fire risk at multiple scales. At a landscape scale, vegetation reflects exposure

to the hazard. Wildfire behavior is obviously a function of vegetation amount and configuration, which in turn mediates the potential for wildfire to reach a structure. At the local scale, vegetation plays a role in the structures' sensitivity to the hazard, with different features of the vegetation becoming more important than others.

In this study, we evaluate the relative importance of vegetation cover at local and landscape scales in explaining structure loss from 2013 to 2018 in California—statewide and separately for three of the most fire-prone regions. We compared vegetation metrics along with several human and biophysical variables associated with structure loss at the locations of destroyed and unburned structures within fire perimeters to assess their relative role.

We ask:

- (1) Is vegetation cover substantially greater at locations of destroyed structures than unburned structures? Does this effect vary by region or distance?
- (2) What is the relative importance of vegetation calculated at local and landscape scales in relation to other factors previously associated with structure loss?
- (3) Does structure loss vary across different classes of the wildland–urban interface?
- (4) Do these relationships vary by geographical region within California?

2. Materials and Methods

2.1. Structure Locations and Study Regions

We acquired the locations of destroyed structures via a public records request to Cal Fire, and divided them into three regions as in Syphard and Keeley [18] (Figure 1). These included the central and northern coast areas surrounding San Francisco Bay (“Bay Area”), the regions surrounding the northern cismontane Sierra Nevada (“North Interior”), and the region comprising coastal counties south of San Luis Obispo (“Southern California”). To derive data for unburned structures, we placed a point within the centroid of building polygons that overlaid fire perimeters using the open-access Microsoft Building Footprint dataset (<https://www.microsoft.com/en-us/maps/building-footprints>). For fire perimeters, we used the State of California Fire and Resource Assessment Program (FRAP) fire perimeter data from 2013 to 2018 (<https://frap.fire.ca.gov/frap-projects/fire-perimeters/>). After combining the unburned points with locations of destroyed structures within fires, we took a random sample of the data with a minimum of 500-m distance between points to reduce potential for statistical bias due to overlapping buffers.

2.2. Variables

To measure defensible space in previous studies, researchers have used fine-scale aerial photography to calculate the range of metrics that collectively define the legal definition of defensible space in California [12,13]. Calculating these types of measurements for large numbers across broad scales, however, would be prohibitively time-consuming. Alternatively, remotely sensed satellite imagery can provide unbiased calculations of vegetation biomass that was present before the fire (e.g., [14,16,28]). Here, we calculated the mean annual maximum Normalized Difference Vegetation Index (NDVI) values within three concentric circles around structures, averaged for the two years prior to the fire. Using the annual maximum NDVI and averaging across the two years prior to fire minimized potential uncertainties relative to fine-scale temporal fluctuation from weather variables [29]. We used NDVI data calculated from Landsat remote sensing products, at 30 m spatial resolution, provided by climateengine.org/data. To evaluate whether the distance of measurement differentially influences structure loss, we compared NDVI values from concentric circles surrounding the structure at three distances—30, 90, and 300 m (Table 1). We included all cells overlapping the concentric circles in our calculation of mean NDVI. Due to the resolution of the satellite data, we did not calculate distances shorter than 30 m.

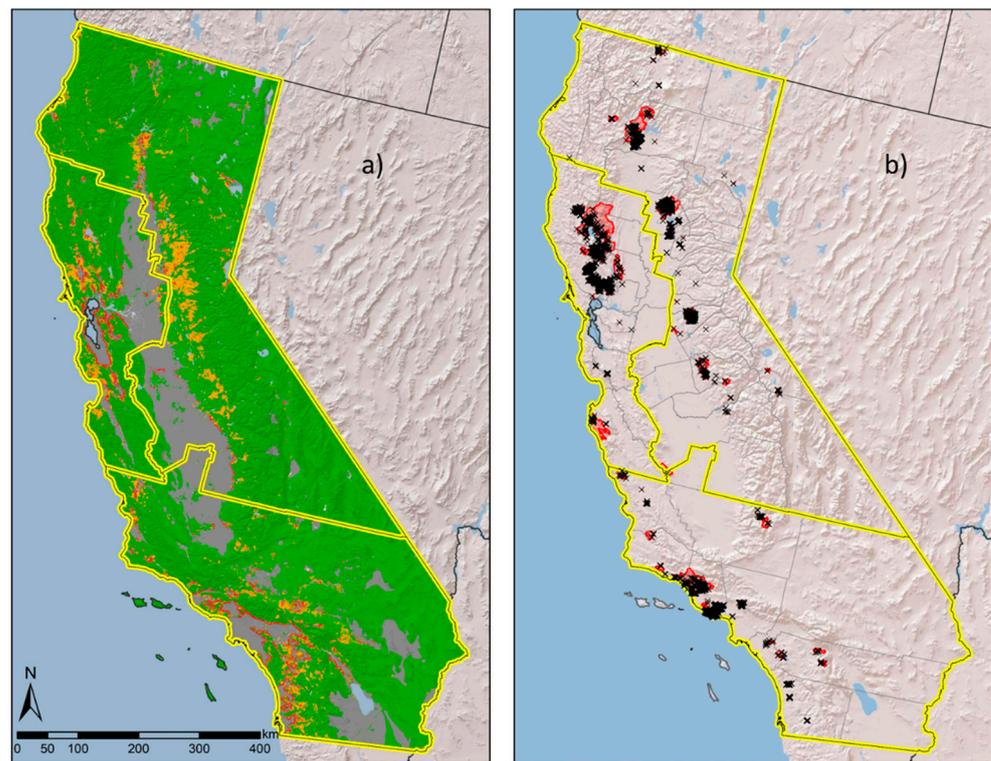


Figure 1. Study area illustrating three California regions: the Bay Area (northwest), the North Interior (northeast), and Southern California (south). The WUI classes in (a) depict Interface WUI (red), Intermix WUI (orange), Unvegetated (gray), and Low-density vegetated (green). The fires included in the study (red perimeters) and location of destroyed structures (black) are shown in (b). Hillshade basemap from ArcGIS Online (<https://www.arcgis.com/index.html>).

To represent landscape-level vegetation pattern, we used a landscape pattern metric to calculate the proportion of highly flammable vegetation within a circular moving window at a 2.5 km radius (the approximate distance the wind may carry an ember [8]) around all structures (as in Alexandre et al. [19]), using Fragstats v4.2.1 [30]. For this variable, we used the U.S. Geological Survey National Land Database (NLCD, mrlc.gov) from 2016 to create a binary class of flammable versus non-flammable vegetation, grouping together grass, shrubs, and trees into flammable vegetation.

The variable that represents the landscape-level pattern of houses and vegetation together is the WUI. For each structure, we used the 2010 WUI map created by Radeloff et al. [23] to extract the corresponding WUI class in which it was located. Intermix WUI is defined as areas in census blocks that have ≥ 6.18 houses per km^2 and ≥ 50 percent cover of wildland vegetation. Interface WUI is defined as areas with ≥ 6.18 houses per km^2 with large areas (at least 5 km^2) of at least 75% vegetation within 2.4 km. In addition to Intermix and Interface WUI, we grouped unvegetated classes together (including inhabited and uninhabited areas at different housing densities) and areas that were vegetated, either uninhabited or inhabited, but with housing density lower than $6.18 \text{ structures km}^2$.

Table 1. Name and description of explanatory variables used to explain structure loss in California.

	<i>Variable Name</i>	<i>Definition</i>	<i>Source</i>	<i>Resolution</i>
<i>Climate</i>	Actual evapotranspiration (AET)	Average AET (Water available between wilting point and field capacity; mm), 1981–2020	Flint and Flint [31]	270 m
	MaxTemp	Average Maximum Monthly Temperature (deg. C), Annual, 1981–2010	Flint and Flint [31]	270 m
<i>Topography</i>	Elevation	Elevation (m)	U.S. Geological Survey	30 m
	Topographic heterogeneity	The range in elevation values from a center cell and the three-cell radius immediately surrounding it using a digital elevation model. Values were converted to a 0–1 scale using the standard deviation.	NatureServe (https://databasin.org)	90 m
<i>Human</i>	Dist_powerline	Euclidean distance from electric transmission lines (status = operational AND type = OH; m)	California Energy Commission	30 m
	Dist_rd	Euclidean distance from roads (excluding 4WD and OHV; m)	TIGER/Line 2016 (www.census.gov)	30 m
<i>Vegetation</i>	NDVI_30	Mean NDVI max averaged for 1 and 2 years before fire across 30 m buffer around structure	Climate Engine (http://climateengine.org/)	30 m
	NDVI_90	Mean NDVI max averaged for 1 and 2 years before fire across 90 m buffer around structure	Climate Engine (http://climateengine.org/)	30 m
	NDVI_300	Mean NDVI max averaged for 1 and 2 years before fire across 300 m buffer around structure	Climate Engine (http://climateengine.org/)	30 m
	Flammable veg in 2.5 km	Proportion highly flammable vegetation (grass, trees, and shrubs) across circular moving window with 2.5 km radius	NLCD 2016 Land Cover www.mrlc.gov	30 m
<i>Vegetation and human</i>	WUI Class	Intermix, Interface, Unvegetated; Low-density vegetated	Radeloff et al. [23]	Polygon converted to 30 m grid

In addition to the vegetation-related variables, we explored other biophysical and human factors as potential predictors (Table 1). Given their demonstrated overall relationship with the spatial distribution of fire probability [4,32–34], we considered two long-term climate variables—average maximum monthly temperature from 1981 to 2010 and average actual evapotranspiration (AET), a measure of the water available between wilting point and field capacity (mm), 1981–2010. We also included two topographic variables, which mediate fire behavior and vegetation properties: elevation and topographic heterogeneity. The elevation grid was provided by LANDFIRE (landfire.gov/elevation.php) at 30 m resolution and the topographic heterogeneity index was calculated from a 90 m digital elevation model (DEM) to capture surrounding diversity in terrain (<https://databasin.org/datasets/1f86100938b544a3b6361eee6ac05945/>). Finally, we included two anthropogenic variables to assess their relative influence on structure loss. These included distance to roads, which can serve as a proxy for firefighter access, derived using the 2015 TIGER Roads data, U.S. Dept. of Commerce, U.S. Census Bureau (www.census.gov), and distance from electric transmission line, with data provided by the California Energy Commission, Electric Transmission Lines (https://cegis-caenergy.opendata.arcgis.com/datasets/260b4513acdb4a3a8e4d64e69fc84fee_0). We also included distance to powerline because several of the recent destructive fires were ignited by powerlines. As the building characteristics provided by Cal Fire for destroyed structures were not available for the unburned homes within the fire perimeter, we did not incorporate these into our analysis, as these numbers are available in Syphard and Keeley [18].

2.3. Analysis

Statewide and for the three regions, we summarized and compared the average NDVI within the buffer distances around destroyed and unburned structures. Although we used the spatially filtered data to ensure more robust statistical analysis, we assembled these summary statistics for the full dataset to reflect the full population. We additionally

summarized all point data for destroyed and unburned structures according to their WUI classification.

To quantify the relative importance of the explanatory variables, we developed generalized linear regression models (GLMs) [35] for single predictor variables using a logit link and a binomial response, i.e., destroyed versus unburned structures, as in Syphard and Keeley [18]. We then calculated the deviance explained (D^2) for each variable, a comparable metric to R-squared in linear regression. Given that the WUI data were presented in different classes, we also calculated the relative risk (RR) [36] among all class pairs to determine if there were significant differences in risk and to identify which classes were most strongly associated with destroyed structures. The RR is based on the ratio of pairwise class proportions (i.e., destroyed versus unburned structures in each WUI class) and identifies whether classes have the same risk (a value of 1), or if one class has a higher (values > 1) or lower (values < 1) risk compared to another.

We developed statewide and regional multivariate classification trees using the RPART package (<https://cran.r-project.org/web/packages/rpart/rpart.pdf>) in RStudio version 1.1463 ([rstudio.com](https://www.rstudio.com)) to assess the relative importance of variables in terms of how well they split the data between destroyed and unburned structures. Classification trees are also useful for illustrating variable effects and interactions in a multi-variate environment [37]. Given the large number of potential predictor variables, we only performed this analysis statewide to ensure sufficient sample size. There was a strong correlation ($r > 0.7$) between the NDVI measurements in different buffer sizes, so we only evaluated NDVI at the 30 m buffer distance, as that was the measurement with the largest difference between destroyed and unburned structures. Additionally, elevation was correlated with mean annual temperature ($r = -0.8$), so we removed that variable because temperature is a more direct measurement of the spatial distribution of climatic variability. There were no other high correlations among explanatory variables. Thus, the variables that we included in the tree were: NDVI, topographic heterogeneity, distance to roads, distance to powerlines, WUI class, mean annual maximum temperature, mean actual evapotranspiration, and vegetation within 2.5 km. We pruned the trees using the complexity parameter that best minimized overfitting with the smallest cross-validated error and calculated model performance of the training data using the area under the curve (AUC) for receiver operating characteristic plots (ROC) [38].

3. Results

The comparison of destroyed versus unburned structures did not reveal a strong influence of surrounding vegetation as measured through NDVI statewide or in the Bay Area (Figures 2 and 3). There, and in Southern CA where the differences were larger, the NDVI was greater for destroyed structures than unburned structures at all three buffer distances. However, the differences among buffer distances were minimal, with a larger separation of destroyed and unburned structures at 30 m than the other two distances. In the North Interior region, the relationship was inverse in that there was greater NDVI in unburned than destroyed structures at all three buffer distances (Figure 2).

The ranking of the deviance explained for surrounding vegetation compared to other explanatory variables was low statewide and in all regions except for Southern CA, where the deviance explained for NDVI in the 30-m buffer was the top-ranking explanatory variable (Figure 3). In all cases, the amount of vegetation within 30 m was relatively more important than that in 90 or 300 m. The broader metric of vegetation, at 2.5 km, explained more than NDVI statewide and in the North Interior.

Vegetation pattern combined with housing pattern—as measured through the WUI—was consistently more important than the other vegetation-related variables, and it was one of the top two ranking variables for all analyses in all regions (Figure 3). The ranking of the non-vegetation variables varied from region to region, although elevation was one of the top two variables along with WUI class statewide (Figure 3). Otherwise, distance to powerline was one of the top two variables in the Bay Area, maximum average temperature

was the highest-ranking variable in the North Interior, and NDVI at 30 m was one of the top two variables in Southern California.

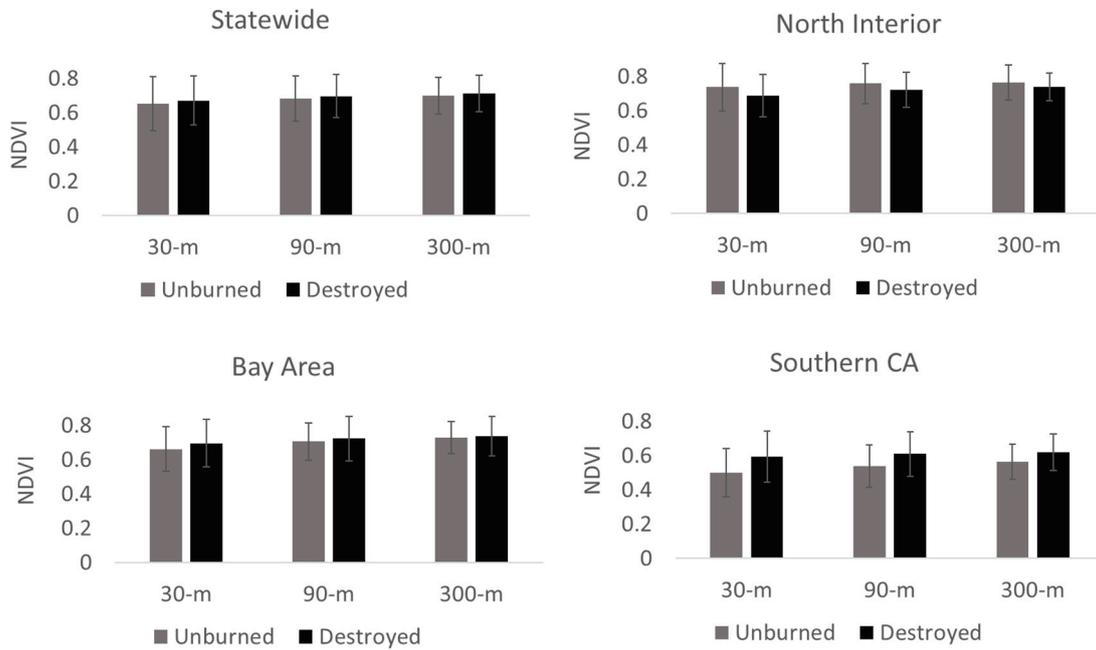


Figure 2. Mean NDVI in unburned and destroyed structures in wildfire perimeter statewide and in three regions of California. Error bars depict the standard deviation.

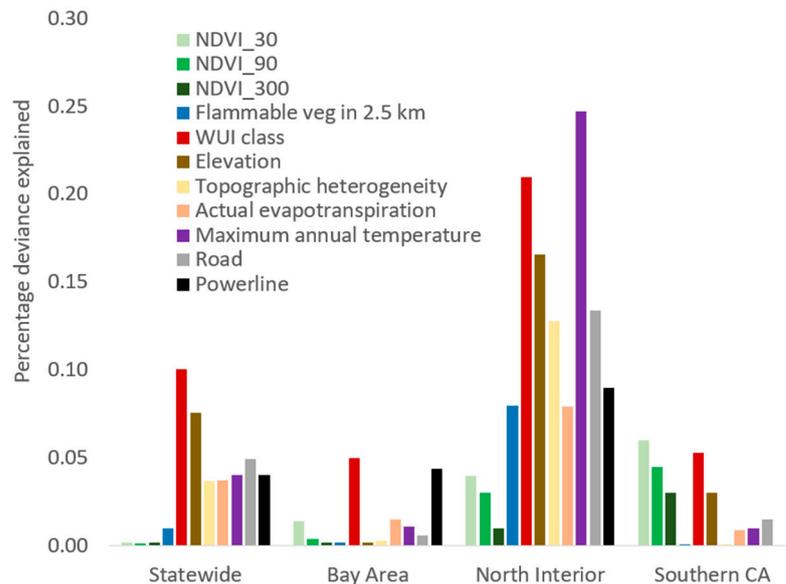


Figure 3. Percentage deviance explained for unburned versus destroyed structures in binomial regression models statewide and for three regions in California. The numbers following “NDVI” represent the buffer distance surrounding structures for which the Normalized Difference Vegetation Index (NDVI) was calculated.

Of the four WUI classes evaluated, the Intermix WUI and Low-density vegetated classes were the most common for all structures in the analysis (Figure 4). Most of the unburned structures were distributed in the Low-density vegetated class while most of the destroyed structures were distributed within the Intermix WUI class. The RR assessment within different WUI classes showed that the Intermix WUI had disproportionately larger

numbers of destroyed structures than the three other classes statewide (RR = 1.15–2.5) and in all three regions (RR = 1.14–1.95), except for the Bay Area (RR = 0.93) and the North Interior (RR = 0.89) study areas, where there were disproportionately fewer destroyed structures in the Intermix versus the Interface WUI classes (Table 2). Although all comparisons at the statewide scale were significant, the Intermix versus Interface comparisons were not significant for the three regions separately or for the Intermix versus Unvegetated class in the Bay Area. Among other classes, Interface WUI generally had disproportionately more destroyed structures than the two non-WUI classes, unvegetated and low-density vegetated (RR = 1.29–4.64). The vegetated class had consistently lower RR than the unvegetated class (RR = 0.5–0.79).

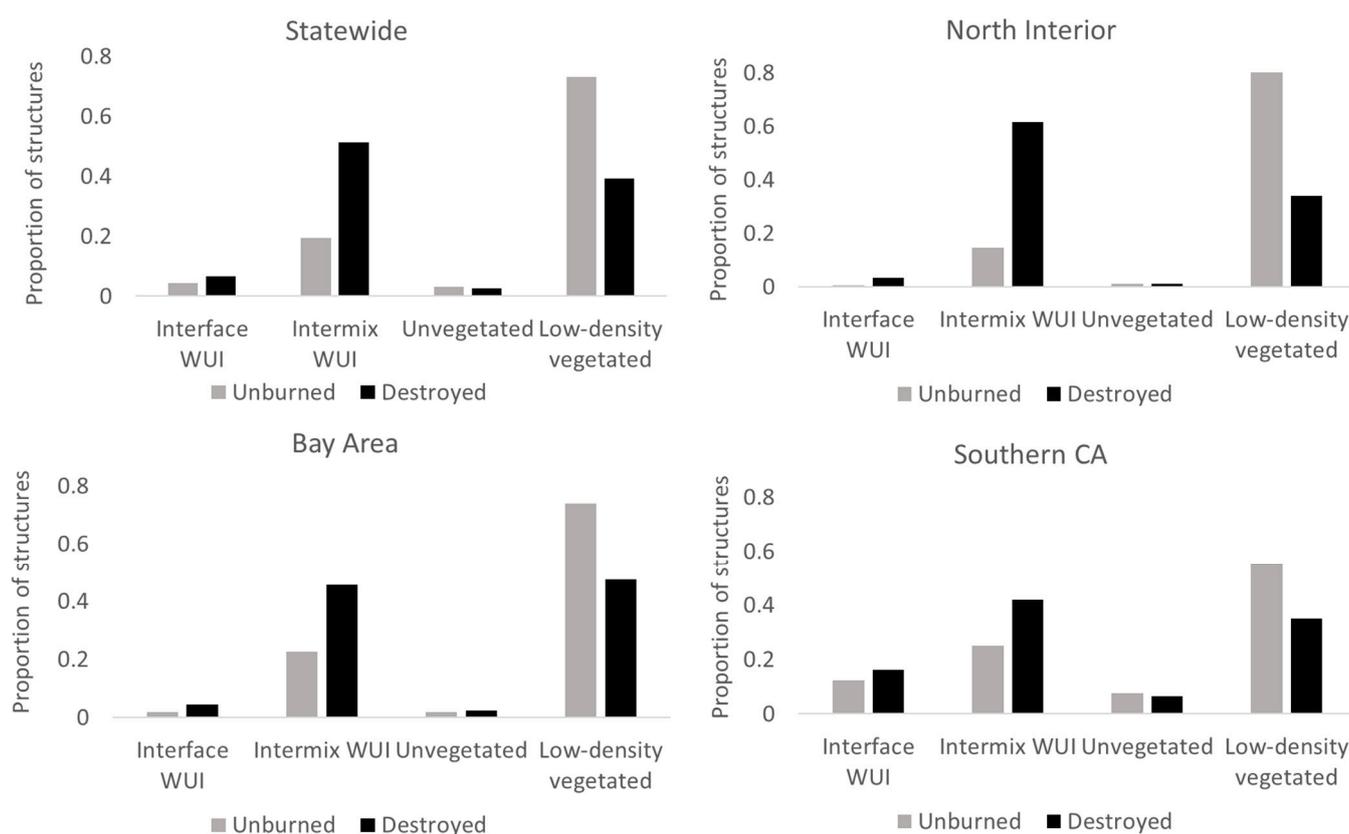


Figure 4. Proportion of unburned and destroyed structures distributed among four Wildland–Urban Interface cover classes statewide and in three regions of California.

Table 2. Relative risk (RR) among WUI classes statewide and for three California regions. In the class comparisons, an RR > 1 means the first class listed had disproportionately more destroyed than unburned structures; < 1 means the first class listed had disproportionately fewer destroyed than unburned structures; and 1 means no difference between the two classes.

	Statewide	p-Value	Bay Area	p-Value	North Interior	p-Value	Southern CA	p-Value
<i>Intermix vs. Interface</i>	1.22	<0.001	0.93	0.4	0.89	0.25	1.14	0.2
<i>Intermix vs. Unvegetated</i>	1.15	<0.001	1.17	0.31	1.17	0.01	1.55	0.009
<i>Intermix vs. Low-density vegetated</i>	2.25	<0.001	1.66	<0.001	4.14	<0.001	1.95	<0.001
<i>Interface vs. Unvegetated</i>	0.96	0.004	1.29	0.19	2.34	0.006	1.34	0.11
<i>Interface vs. Low-density vegetated</i>	1.85	<0.001	1.78	<0.001	4.64	<0.001	1.7	<0.001
<i>Vegetated vs. Unvegetated</i>	0.51	<0.001	0.71	0.03	0.5	0.02	0.79	0.177

The classification trees showed that statewide, the WUI was the most influential factor separating destroyed from unburned structures (Figure 5), and in this case, the two WUI types, Intermix and Interface, were two types associated with destroyed versus unburned structures. The second split in the data was NDVI within a 30-m buffer, with destroyed structures tending to occur above a threshold of 0.49. The last variable selected in the tree was mean annual maximum temperature, with destroyed structures tending to occur in areas that average between 20 and 23 degrees Celsius. The AUC for this tree was 0.68.

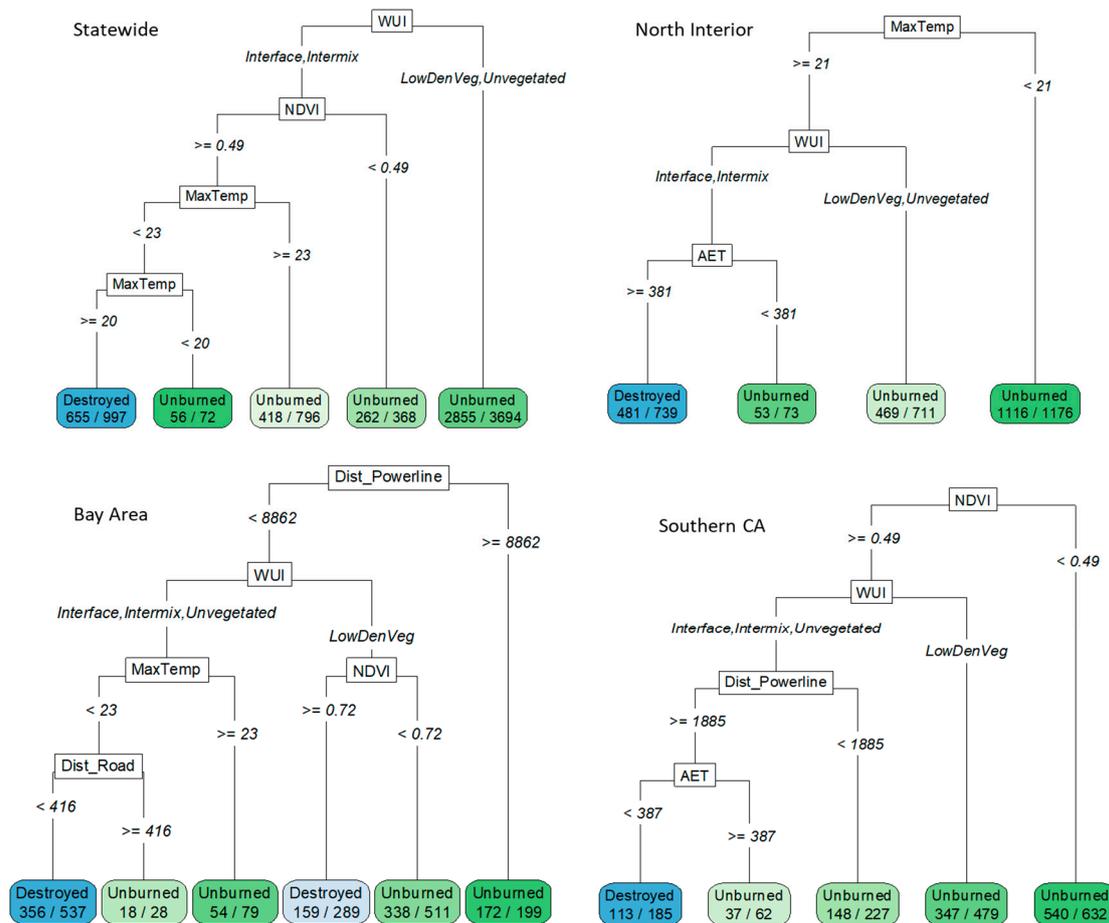


Figure 5. Classification trees illustrating variables explaining unburned versus destroyed structures statewide and for three California regions. The NDVI variable is for 30 m distance around structures (90 and 300 m not included). The intensity of the blue and green node colors is proportional to the percentage of observations. For variable explanations, refer to Table 1.

The separate classification trees for each region showed variability in the factors that best separated the destroyed from unburned structures (Figure 5). In all cases except Southern CA, landscape-scale factors related to spatial distribution and exposure were responsible for the first split in the data, and WUI was the second split in the data, followed by other variables. For the North Interior region, the first split was maximum average temperature, followed by WUI class—again with Interface and Intermix separating destroyed from unburned structures, and mean actual evapotranspiration. The training AUC for the tree in this region was 0.84. In the Bay Area, the first split was distance to powerline followed by WUI class in which Interface, Intermix, and Unvegetated were grouped together as those best separating destroyed from unburned structures. Depending on which WUI class the structure belonged to, the final splits were for mean annual maximum temperature and distance to road or NDVI. The AUC for the Bay Area tree was 0.70. In Southern California, the first split in the data was the amount of vegetation within 30 m of the structure, with an NDVI of >= 0.49 being the threshold. In this region, the WUI was the second most

important split, followed by distance to powerline and mean annual evapotranspiration, again with Unvegetated combined with Intermix and Interface defining the split in data. The AUC for this tree was 0.69.

4. Discussion

Vegetation is the primary means by which wildfire propagates; is something that can be managed; and thus, is often considered key among strategies to reduce wildfire risk. Yet, the relationship between vegetation and structure loss is complex, and this study underlines the fact that vegetation has different relationships with fire risk at different scales, representing different operative mechanisms. These relationships also vary in relative effect depending upon geographical region. Overall, landscape-level vegetation and housing pattern provided better separability of unburned and destroyed structures across the state than local-scale vegetation amount. None of the variables analyzed, however, had deviance explained higher than 25%, which reaffirms the notion that structure loss is a function of multiple factors interacting simultaneously, including factors not explored here.

Although multiple definitions of the WUI have been proposed and incorporated into policy, even explicitly accounting for fire risk [27], the underlying conceptual premise for most definitions that focus on fire is that risk and ignitions are likely to be higher where houses meet or intermingle with vegetation [23,39–42]. Thus, the two conditions that must be present are vegetation and housing, with different classes of WUI defined based on variations in housing density and vegetation cover.

In previous studies examining structure loss probability, housing location and pattern have consistently been found to be top-ranked among a wide range of explanatory variables [4,6,19,43]. Although the specific structural pattern and housing density where risk is highest vary geographically [4,6,19], lower-density housing at a landscape scale has been the most consistent housing pattern with the highest risk. The reason for the strong significance of housing variables, particularly ones that reflect dispersed or low-density housing, is that they represent high exposure to wildfire, which is the first condition that must be met for structure loss to occur [5,20]. If a fire does not reach a structure, the other factors become irrelevant.

A primary reason explaining why low- to intermediate-density housing is so strongly tied to fire risk is because these are the houses most likely to be adjacent to flammable wildland vegetation—and this is what creates the exposure. This is also the reason that the WUI as defined here is so strongly associated with fire risk [23]—because it is a measurement that combines housing with adjacency and distance to wildland vegetation [44]. The WUI definition incorporates a measurement of vegetation out to 2.4 km, and this variable was more influential than our measurement of vegetation to 2.5 km, which suggests it is the specific pattern of houses and vegetation that matter most—more than vegetation by itself.

In this study, the largest proportion of destroyed structures was in the Intermix WUI class, followed by the non-WUI, low-density, vegetated class. Intermix also had the highest RR compared to Interface and non-WUI classes statewide. Regionally, however, the relative ranking between Intermix and Interface varied, and the differences were non-significant. Both Intermix and Interface WUI had higher RRs than the other two non-WUI classes across all regions.

This finding, that WUI classes have disproportionately higher fire risk than non-WUI classes, and that relationships vary by region and scale, has been observed in other empirical studies. Kramer et al. [24] found that, across the United States, the majority of destroyed and threatened structures were within areas designated as WUI, but a large proportion of destroyed structures were also in non-WUI areas with housing density that was too low to meet the definition of WUI defined here. Ciggiano et al. [44] also found that most buildings lost in recent fires across the US from 2000 to 2018 were within WUI-designated areas. Furthermore, all destroyed structures in their study were close to wildland vegetation (from 100 to 850 m), and more burned buildings were in the Intermix rather than the Interface. On the other hand, Kramer et al. [25] found that from 1985 to 2013

in California, more structures were destroyed in Interface rather than Intermix WUI; that is, in areas with less wildland vegetation. This empirical research on WUI types is generally consistent with the finding that low-intermediate housing density is where most structures are destroyed [4,43]; but clearly there are regional, and perhaps temporal, differences in the relative importance of the predominant type of WUI.

The geographical differences in the relative housing density or type of WUI where structure loss is most likely to occur likely reflects the influence of other factors that combine to contribute to structure loss probability, and the fact that fires tend to be idiosyncratic. For example, in several recent California fires, the role of winds and structural characteristics of buildings were clearly dominant factors. While the average structure density where structures were lost fires was low, there were also portions of the fires evaluated here in which significant structure-to-structure spread occurred throughout high-density housing. High housing density that facilitates structure-to-structure spread has been observed in other fires with large numbers of destroyed buildings [10,45], in part because certain structural features and surrounding materials can facilitate fire spread [46].

The difference between a structure surviving and being destroyed could also be due to factors that have yet to be quantified, such as firefighter presence or serendipitous factors such as a sudden shift in wind velocity or direction. The scale of measurement can also affect the relative importance of different housing and vegetation patterns [11]. Different regions have different baseline housing densities with unique arrangements of housing interspersed with vegetation. Empirical studies have also been conducted at different spatial scales, where the average housing density may vary with the overall range and variation of the structures in the sample.

Comparison of destroyed with unburned structures may also yield different results depending upon whether the unburned structures are within fire perimeters as they are in this study. That is, if housing density and the WUI are indices of exposure to fire, houses in the perimeter are already biased in that they have been exposed. This is likely why the second most common WUI class in this study was non-WUI low-density vegetated housing.

This study also shows that structure exposure to wildfire can be a function of other sources of spatial variation across a landscape. Depending upon the region, factors such as elevation, climatic variation as measured by maximum annual temperature, and distance to powerline were similar in variable importance to WUI class. These factors illustrate how parts of some landscapes are more fire-prone than others, and that structure loss tends to occur in the most fire-prone facets of a landscape. For example, the importance of temperature in the North Interior likely reflects how climatic variation is a strong driver of fire activity in this region of California [47], and structures were destroyed more often in areas with hotter temperatures. Given that the most destructive fires in the Bay Area were caused by powerline ignitions, spatial proximity to powerline was a strong separator of unburned and destroyed structures in that region. In Southern CA, distance to powerline was one of the lower-ranking variables included in the classification tree, and the direction of the relationship was counter-intuitive. This may reflect the lower number of destructive powerline-ignited fires during the study period here; it may also reveal an interaction with the higher-ranking variables in the tree, suggesting powerline proximity is serving as a proxy for something else. As the definition of WUI used here is a function of housing and vegetation alone, other approaches that additionally account for variation in fire risk [27] or that are scaled for specific geographies [44] may be even more useful for planning purposes.

The one region in which local-scale vegetation amount explained structure loss better than landscape-scale vegetation pattern (i.e., the WUI) was Southern CA. The classification tree showed that NDVI at 30 m was the first split in the classification tree, followed by the WUI. This result is somewhat surprising because Southern CA has the largest extent of WUI of the three regions. Additionally, in Southern CA, housing density was found to explain more variation in structure loss than other factors, including defensible space [48]. However, it may be that the extensive nature of WUI in the region may partly explain why it was second in importance to local-scale vegetation. Here and in the Bay area,

unvegetated areas (largely urban) were included with the WUI class in the first split of the classification tree, suggesting that these fires were all at least partially surrounded by high-density development, and there may not be much variability in the spatial pattern of development where the fires in this study occurred. It may also suggest structures with large amounts of exotic landscaping in urban areas are most at risk in this region.

The use of NDVI to measure local vegetation amount was appropriate for a broad-scale study such as this, to rank the relative importance of factors across large regions; and while NDVI captures vegetation abundance, it cannot distinguish vegetation type, condition, or structure, all of which are important for fire behavior [49]. NDVI also cannot indicate where abundance is high within a 30 m grid cell. The empirical studies evaluating the role of defensible space in this region used a wide range of factors to quantify defensible space at scales much finer than 30 m [12,13], and these studies found that the most effective distance of defensible space is shorter than 30 m, particularly when vegetation is touching or overhanging a structure.

That vegetation is most important closer to the house may be seen in this study in that the deviance explained was smaller for larger buffer distances; however, given the low overall deviance explained, further analysis is needed. A regional study exploring four of the fires included in the two northern regions of our analysis also found that vegetation cover near the structure, as measured by NDVI within a 25 m buffer, was an important predictor of structure loss. However, wind speed dampened the relationship to the point that all vegetation classes in that study had loss rates above 80% [50]. Syphard and Keeley [18] found that defensible space distance was much less important than structural characteristics and speculated that this result might be because the distances measured were not at fine enough scales to capture the importance of vegetation close to the structure. Another important component of defensible space is irrigation and vegetation moisture. Gibbons et al. [17] found that irrigation and vegetation arrangement can be just as effective as minimizing vegetation amount. This is likely because wind-borne embers are more likely to be extinguished if they land on something with high fuel moisture.

Although we did not repeat the analysis here, Syphard and Keeley [18] found that structural characteristics play an important role in protecting structures once a fire reaches there. This may also reflect how preventing ember entry to the building may be one of the most significant factors in increasing probability of survival. In that study and this one, none of the factors we evaluated explained a substantial amount of variation in destroyed structures.

The low deviance explained may be due to uncertainty introduced with spatial data or a low overall variability in our spatial data. As all structures in our analysis had been, to some extent, exposed to a fire, the measurements of exposure used here, such as the WUI, distance to roads, or broad climatic variation, are only able to explain the difference between degrees of exposure. The reason for this restriction was that we could not compare pre-fire NDVI with structures that did not have a fire. Nevertheless, given the many large fires in this study, factors such as distance to powerline or road, or the distance to the ignition location, can still vary significantly across the dataset. We are unsure why the deviance explained was higher overall for the North Interior region, but it may reflect a higher vegetation heterogeneity in the fire perimeters than the other regions, given that conifer forest is more prevalent here. The low deviance overall also suggests, as mentioned previously, that a range of other characteristics play into the ultimate outcome of a fire event. Thus, this research illustrates differences in the relative importance of the variables analyzed, but additional work and more extensive empirical research will be needed to obtain a full understanding of why some structures are destroyed in fires and others are not.

5. Conclusions

There are multiple ways that vegetation can influence fire risk. At broad scales, vegetation pattern is an important determinant of exposure. At finer scales, vegetation affects sensitivity to the hazard and mediates fire behavior through fuel load (i.e., amount)

or fuel moisture and flammability [20]. Our comparison of vegetation pattern and amount generally identified the pattern of vegetation and housing to better explain structure loss than local-scale vegetation amount. This is likely because exposure to fire is a necessary first condition determining structure survival, and sensitivity is only relevant once the fire reaches a structure. This finding could help develop the ranking of regions for focus of fire management efforts. These results also suggest that the most effective fire risk reduction approach will account for multiple factors at multiple scales and will incorporate multiple simultaneous strategies. The widespread geographical variability in results reinforces the notion that “one size does not fit all”. Our study indicates that effective fire management plans will need additional customized, local-scale empirical research on specific vegetation characteristics relative to structure loss.

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References

- Haynes, H.J.G. *Fire Loss in the United States during 2014*; National Fire Protection Association, Fire Analysis and Research Division: Quincy, MA, USA, 2015.
- Blanchi, R.; Lucas, C.; Leonard, J.; Finkele, K. Meteorological conditions and wildfire-related house loss in Australia. *Int. J. Wildl. Fire* **2010**, *19*, 914–926. [[CrossRef](#)]
- Molina-Terrén, D.M.; Xanthopoulos, G.; Diakakis, M.; Ribeiro, L.; Caballero, D.; Delogu, G.M.; Viegas, D.X.; Silva, C.A.; Cardil, A. Analysis of forest fire fatalities in Southern Europe: Spain, Portugal, Greece and Sardinia (Italy). *Int. J. Wildl. Fire* **2019**, *28*, 85–98. [[CrossRef](#)]
- Syphard, A.D.; Rustigian-Romsos, H.; Mann, M.; Conlisk, E.; Moritz, M.A.; Ackerly, D. The relative influence of climate and housing development on current and projected future fire patterns and structure loss across three California landscapes. *Glob. Environ. Chang.* **2019**, *56*, 41–55. [[CrossRef](#)]
- Syphard, A.D.; Keeley, J.E. Why are so many structures burning in California. *Fremontia* **2020**, *47*, 28–35.
- Alexandre, P.M.; Stewart, S.I.; Mockrin, M.H.; Keuler, N.S.; Syphard, A.D.; Bar-Massada, A.; Clayton, M.K.; Radeloff, V.C. The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of California and Colorado. *Landsc. Ecol.* **2015**, *31*, 415–430. [[CrossRef](#)]
- Foote, E.I.D.; Martin, R.E.; Gilles, J.K. The defensible space factor study: A survey instrument for post-fire structure loss analysis. In Proceedings of the 11th Conference on Fire and Forest Meteorology, Missoula, MT, USA, 16–19 April 1991; Andrews, P.L., Potts, D.F., Eds.; Society of American Foresters: Bethesda, MD, USA, 1991.
- Cohen, J.D. Home ignitability in the wildland-urban interface. *J. For.* **2000**, *98*, 15–21.
- Cohen, J. Relating flame radiation to home ignition using modeling and experimental crown fires. *Can. J. For. Res.* **2004**, *34*, 1616–1626. [[CrossRef](#)]
- Maranghides, A.; Mell, W. *A Case Study of a Community Affected by the Witch and Guejito Fires*; National Institute of Standards and Technology: Gaithersburg, MD, USA, 2009.
- Braziunas, K.H.; Seidl, R.; Rammer, W.; Turner, M.G. Can we manage a future with more fire? Effectiveness of defensible space treatment depends on housing amount and configuration. *Landsc. Ecol.* **2021**, *36*, 309–330. [[CrossRef](#)]
- Syphard, A.D.; Brennan, T.J.; Keeley, J.E. The role of defensible space for residential structure protection during wildfires. *Int. J. Wildl. Fire* **2014**, *23*, 1165–1175. [[CrossRef](#)]
- Miner, A. *Defensible Space Optimization for Preventing Wildfire Structure Loss in the Santa Monica Mountains*; Johns Hopkins University: Baltimore, MD, USA, 2014.
- Platt, R.V. Wildfire hazard in the home ignition zone: An object-oriented analysis integrating LiDAR and VHR satellite imagery. *Appl. Geogr.* **2014**, *51*, 108–117. [[CrossRef](#)]
- Penman, S.H.; Price, O.F.; Penman, T.D.; Bradstock, R.A. The role of defensible space on the likelihood of house impact from wildfires in forested landscapes of south eastern Australia. *Int. J. Wildl. Fire* **2018**, *28*, 4–14. [[CrossRef](#)]

16. Gibbons, P.; van Bommel, L.; Gill, A.; Cary, G.J.; Driscoll, D.A.; Bradstock, R.A.; Knight, E.; Moritz, M.A.; Stephens, S.L.; Lindenmayer, D.B. Land management practices associated with house loss in wildfires. *PLoS ONE* **2012**, *7*, e29212. [CrossRef]
17. Gibbons, P.; Gill, A.M.; Shore, N.; Moritz, M.A.; Dovers, S.; Cary, G.J. Options for reducing house-losses during wildfires without clearing trees and shrubs. *Landsc. Urban Plan.* **2018**, *174*, 10–17. [CrossRef]
18. Syphard, A.D.; Keeley, J.E. Factors associated with structure loss in the 2013–2018 California wildfires. *Fire* **2019**, *2*, 49. [CrossRef]
19. Alexandre, P.M.; Stewart, S.I.; Keuler, N.S.; Clayton, M.K.; Mockrin, M.H.; Bar-Massada, A.; Syphard, A.D.; Radeloff, V.C. Factors related to building loss due to wildfires in the conterminous United States. *Ecol. Appl.* **2016**, *26*, 2323–2338. [CrossRef] [PubMed]
20. Schumann, R.L.; Mockrin, M.; Syphard, A.D.; Whittaker, J.; Price, O.; Johnson, C.; Emrich, C.T.; Butsic, V. Wildfire recovery as a “hot moment” for creating fire-adapted communities. *Int. J. Disaster Risk Reduct.* **2019**, *42*, 101354. [CrossRef]
21. Blanchi, R.; Leonard, J.E. Investigation of Bushfire Attack Mechanisms Involved in House Loss in the ACT Bushfire 2003. Bushfire CRC Report CMIT-2005-377. Available online: https://www.bushfirecrc.com/sites/default/files/downloads/act_bushfire_crc_report.pdf (accessed on 11 March 2021).
22. Radeloff, V.C.; Hammer, R.B.; Stewart, S.I.; Fried, J.S.; Holcomb, S.S.; McKeefry, J.F. The wildland-urban interface in the United States. *Ecol. Appl.* **2005**, *15*, 799–805. [CrossRef]
23. Radeloff, V.C.; Helmers, D.P.; Anu Kramer, H.; Mockrin, M.H.; Alexandre, P.M.; Bar-Massada, A.; Butsic, V.; Hawbaker, T.J.; Martinuzzi, S.; Syphard, A.D.; et al. Rapid growth of the US wildland-urban interface raises wildfire risk. *Proc. Natl. Acad. Sci. USA* **2018**, *115*, 3314–3319. [CrossRef] [PubMed]
24. Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Stewart, S.I.; Radeloff, V.C. Where wildfires destroy buildings in the US relative to the wildland–urban interface and national fire outreach programs. *Int. J. Wildl. fire* **2018**, *27*, 329–341. [CrossRef]
25. Kramer, H.A.; Mockrin, M.H.; Alexandre, P.M.; Radeloff, V.C. High wildfire damage in interface communities in California. *Int. J. Wildl. Fire* **2019**, *28*, 641. [CrossRef]
26. Bar-Massada, A.; Radeloff, V.C.; Stewart, S.I. Biotic and abiotic effects of human settlements in the wildland-urban interface. *Bioscience* **2014**, *64*, 429–437. [CrossRef]
27. Miranda, A.; Carrasco, J.; González, M.; Pais, C.; Lara, A.; Altamirano, A.; Weintraub, A.; Syphard, A.D. Evidence-based mapping of the wildland-urban interface to better identify human communities threatened by wildfires. *Environ. Res. Lett.* **2020**, *15*. [CrossRef]
28. Schmidt, J. The Butte Fire: A Case Study in Using LIDAR Measures of Pre-Fire Vegetation to Estimate Structure Loss Rates. *Munich Pers. RePEc Arch.* 2020. Available online: <https://mpra.ub.uni-muenchen.de/99699/> (accessed on 11 March 2021).
29. Gray, M.E.; Dickson, B.G.; Zachmann, L.J. Modelling and mapping dynamic variability in large fire probability in the lower Sonoran Desert of south-western Arizona. *Int. J. Wildl. Fire* **2014**, *23*, 1108–1118. [CrossRef]
30. McGarigal, K.; Marks, B.J. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure. 1995. Available online: <http://www.umass.edu/landeco/research/fragstats/documents/Metrics/Metrics%20TOC.htm> (accessed on 11 March 2021).
31. Flint, A.L.; Flint, L.E. Downscaling future climate scenarios to fine scales for hydrologic and ecologic modeling and analysis. *Ecol. Process.* **2012**, *1*, 2. [CrossRef]
32. Mann, M.; Batllori, E.; Moritz, M.; Waller, E.; Berck, P.; Flint, A.; Flint, L.; Dolfi, E. Incorporating anthropogenic influences into fire probability models: Effects of human activity and climate change on fire activity in California. *PLoS ONE* **2016**, *11*, e0153589. [CrossRef]
33. Krawchuk, M.A.; Moritz, M.A.; Parisien, M.-A.; Van Dorn, J.; Hayhoe, K. Global Pyrogeography: The Current and Future Distribution of Wildfire. *PLoS ONE* **2009**, *4*, e5102. [CrossRef]
34. Parisien, M.A.; Moritz, M.A. Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecol. Monogr.* **2009**, *79*, 127–154. [CrossRef]
35. Venables, W.M.; Ripley, B.D. *Modern Applied Statistics with S-Plus*; Springer: New York, NY, USA, 1994.
36. Sheskin, D.J. *Handbook of Parametric and Nonparametric Statistical Procedures*; CRC Press: Boca Raton, FL, USA, 2003; ISBN 1420036262.
37. Breiman, L.; Friedman, J.; Olshen, R.; Stone, C. *Classification and Regression Trees*; Wadsworth: Belmont, CA, USA, 1984.
38. Hanley, J.A.; McNeil, B.J. The meaning and use of the area under a receiver operating characteristics curve. *Radiology* **1982**, *143*, 29–36. [CrossRef]
39. Theobald, D.M.; Romme, W.H. Expansion of the US wildland-urban interface. *Landsc. Urban Plan.* **2007**, *83*, 340–354. [CrossRef]
40. Stewart, S.I.; Radeloff, V.C.; Hammer, R.B.; Hawbaker, T.J. Defining the Wildland–Urban Interface. *J. For.* **2007**, *105*, 201–207.
41. Sirca, C.; Casula, F.; Bouillon, C.; García, B.F.; Ramiro, M.M.F.; Molina, B.V.; Spano, D. A wildfire risk oriented GIS tool for mapping Rural-Urban Interfaces. *Environ. Model. Softw.* **2017**, *94*, 36–47. [CrossRef]
42. Alcasena, F.J.; Evers, C.R.; Vega-Garcia, C. The wildland-urban interface raster dataset of Catalonia. *Data Br.* **2018**, *17*, 124–128. [CrossRef] [PubMed]
43. Syphard, A.D.; Keeley, J.E.; Massada, A.B.; Brennan, T.J.; Radeloff, V.C. Housing arrangement and location determine the likelihood of housing loss due to wildfire. *PLoS ONE* **2012**, *7*, e33954. [CrossRef]
44. Caggiano, M.D.; Hawbaker, T.J.; Gannon, B.M.; Hoffman, C.M. Building loss in wui disasters: Evaluating the core components of the wildland–urban interface definition. *Fire* **2020**, *3*, 73. [CrossRef]

45. Price, O.; Bradstock, R. Landscape scale influences of forest area and housing density on house loss in the 2009 Victorian bushfires. *PLoS ONE* **2013**, *8*, e73421. [[CrossRef](#)] [[PubMed](#)]
46. Caton, S.E.; Hakes, R.S.P.; Gorham, D.J.; Zhou, A.; Gollner, M.J. Review of pathways for building fire spread in the wildland urban interface part I: Exposure conditions. *Fire Technol.* **2017**, *53*, 429–473. [[CrossRef](#)]
47. Keeley, J.E.; Syphard, A.D. Different historical fire-climate patterns in California. *Int. J. Wildl. Fire* **2017**, *26*, 253. [[CrossRef](#)]
48. Syphard, A.D.; Brennan, T.J.; Keeley, J.E. The importance of building construction materials relative to other factors affecting structure survival during wildfire. *Int. J. Disaster Risk Reduct.* **2017**, *21*, 140–147. [[CrossRef](#)]
49. Bond, W.J.; van Wilgen, B. *Fire and Plants*; Chapman & Hall: London, UK, 1996.
50. Schmidt, J. Vegetation Cover and Structure Loss in Four Northern California Wildfires: Butte, Tubbs, Carr, and Camp. 2020. Available online: <https://core.ac.uk/download/pdf/356665112.pdf> (accessed on 11 March 2021).