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What Makes Wildfires Destructive in California?

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Abstract: As human impacts from wildfires mount, there is a pressing need to understand why structures are lost in destructive fires. Despite growing research on factors contributing to structure loss, fewer studies have focused on why some fires are destructive and others are not. We characterized overall differences between fires that resulted in structure loss ("destructive fires") and those that did not ("non-destructive wildfires") across three California regions. Then, we performed statistical analyses on large fires only (≥100 ha) to distinguish the primary differences between large destructive large fires and large non-destructive fires. Overall, destructive fires were at least an order of magnitude larger than non-destructive fires, with the largest area burned varying by season in different regions. Fire severity was also significantly higher in destructive than non-destructive fires. The statistical analysis showed that, in the San Francisco Bay Area and the northern Sierra Nevada foothills, proximity to the Wildland Urban Interface (WUI) was by far the most important factor differentiating destructive and non-destructive wildfires, followed by different combinations of short-term weather, seasonal climate, topography, and vegetation productivity. In Southern California, wind velocity on the day of the fire ignition was the top factor, which is consistent with previous assumptions that wind-driven fires tend to be most destructive and most of the destruction occurs within the first 24 h. Additionally, Southern California's high population density increases the odds that a human-caused wildfire may occur during a severe fire-weather event. The geographical differences among regions and the variation of factors explaining the differences between large destructive and large non-destructive fires reflects the complexity inherent in decision-making for reducing wildfire risk. Land use planning to reduce future exposure of housing development to fire and increased focus on wildfire ignition prevention emerge as two approaches with substantial potential.

Keywords: structure loss; wind-driven fire; wildland-urban interface; fire weather; destructive fire; large fire

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1. Introduction

The changing nature of wildfire has become a prominent ecological and public health issue across the globe, with growing concern that wildfire impacts will accelerate in the near future [1,2]. In response to multiple interacting and geographically varying drivers, fire regimes are changing in diverse ways [3], with area burned increasing in some areas and declining in others [4,5]. In Mediterranean-climate regions, accelerated erosion after megafires can threaten ecosystem regeneration and natural capital recovery [6], but in some conifer forest ecosystems, wildfire reintroduction can provide ecological benefits [7]. Although altered fire regimes have varied with complex ecological effects [8], human consequences are overwhelmingly negative, with impacts to human life and property, public health, culture, and economic systems [9]. Recent fire events have resulted in hundreds of lives lost, tens of thousands of structures destroyed, and exorbitant financial costs [10–13] In California, USA, where structure loss has long been an issue [14], and is getting significantly worse [15], there is a particularly pressing need to understand why structures are lost in destructive fires.

There is a growing body of work documenting important factors contributing to structure loss, particularly in areas like the US and Australia where fires have been most destructive [15–19]. Studies show that structure loss results from a combination of multi-scale factors that vary from region to region [20]. Housing pattern and arrangement are consistently top-ranked correlates [21–23], likely because they reflect exposure to wildfire, which is a necessary first condition for structure loss to occur [24–26]. Accordingly, there is concern over the rapid growth of the Wildland-Urban Interface (WUI), which is where houses meet or intermingle with wildland vegetation [27]. A large proportion of structure loss in the U.S. occurs within areas mapped as the WUI [17,20,28].

Despite the research on factors contributing to structure loss, there has been less study of the fires themselves that cause structures to be destroyed. Lack of specific research focus on destructive fires is likely because it is already assumed that fires where structures are lost are large and wind-driven, burning under extreme meteorological conditions—and this has certainly been the case for many destructive fires in California [29–31] and globally [32,33]. Nevertheless, in fire-prone regions, there are many other large fires that do not become destructive, and there are smaller fires that do. Additionally, the relative importance of fire weather, antecedent climate, terrain, or anthropogenic factors that distinguish between fires that result in structure destruction versus those that do not have yet to be formally quantified. Throughout the paper, we refer to fires that result in at least one structure being destroyed as "destructive".

Fire weather and fuel conditions at the time of the fire are the most obvious concerns when it comes to destructive wildfires, and there has been more than a century of research devoted to the establishment of fire danger rating [34]. A number of different indices for fire danger rating systems have been developed and implemented globally [35–37], and they typically calculate the potential short-term effects of temperature, humidity, wind, and fuel moisture content on fire behavior—to anticipate likelihood of ignition, rate of fire spread, energy release, and difficulty of control.

In addition to short-term factors used to predict fire behavior on a given day, longer-term seasonal climatic variables could potentially predict the likelihood for a destructive fire before or within a given fire season [38]. This is because seasonal climate variables may affect annual variation in fuel amount or moisture. For example, high antecedent precipitation could promote aboveground biomass accumulation [39], or a dry rainy season or hot temperatures could increase the moisture deficit [40]. Seasonal fire-climate relationships are complex, however, and vary in nature and strength and from region to region [41,42].

Beyond dynamic variables such as weather or climate, the geographical location relative to stable landscape features such as topography or human development could explain why some fires become destructive. It is well known that topography mediates fire behavior [43,44], and areas with high topographic diversity may be more prone to erratic fire behavior or conditions that are difficult to control. The geographical relationship between fire and roads is also well established. However, although proximity to roads tends to be positively correlated with ignition occurrence and fire frequency, the relationship with area burned, or large fires, has been inverse in some studies, with larger fires tending to occur in more remote locations, farther from roads [21,45,46]. This is potentially because remote areas may be difficult for firefighters to access for fire suppression efforts [47].

Human-caused ignitions are the dominant ignition source in most of California [47,48], and recent studies have shown the importance of ignition timing with severe wind conditions, such as Santa Ana winds [49,50]. Human-caused ignitions have also been associated with an increase in large fire events [51] in part because human ignitions are likely to occur under a wider range of conditions than lightning-caused fires [52]. Destructive fires are also likely to occur in areas that generally have larger human populations and assets at risk. On one hand, destructiveness may be dampened by proximity to roads for firefighter access. On the other hand, despite potentially improved access to suppression resources, it is possible that the fires that occur closest to humans are the most harmful. Similarly, proximity to the WUI, where fire frequency tends to be highest [53], may be important in explaining the distinction between destructive and non-destructive wildfires.

Understanding the factors that contribute to destructive wildfires is especially important in California, not only because there are so many structures lost there [15], but because management effects and effectiveness vary substantially across the state [54]. California has experienced dramatic changes in its natural fire regimes such that fire frequency has declined dramatically in some areas and increased dramatically in others [55]. Thus, from an ecological perspective, there are benefits to increasing the amount of fire on some landscapes and decreasing the amount of fire on others. From a human safety perspective, however, fires are unambiguously detrimental. Thus, preventing fires is mutually beneficial for humans and resources in the southern part of the state. However, in areas in which fire is beneficial, differentiating between those fires that are harmful to humans and those that have resource benefits remains a challenge. In those areas, there is a need to coexist with fire such that ecologically beneficial fires can remain on the landscape with minimal risks to humans [56]. Regardless, the combination of climate change [40] and the expansion of the WUI 27 are generating concern that more wildfires may convert into megafires and become increasingly destructive [57].

To better understand why some fires become destructive and others do not, we classified wildfires as destructive or non-destructive for three fire-prone California regions and quantified their differences. First, after overlaying fire perimeters from 2000 to 2018 with geographical coordinates of structures destroyed during the same years, we differentiated destructive wildfires, where at least one structure was destroyed, from non-destructive wildfires. We then characterized the differences in fire size and severity and extracted values of potential explanatory variables from within fire perimeters. Assuming that most destructive fires are relatively large, we factored out fires ≥100 ha and performed statistical analyses to explain the differences in large destructive and non-destructive wildfires. Relative to California we asked:

(1) What are the main differences between destructive fires and non-destructive fires?
(2) What combination of fuel, weather, climate, topographic, and anthropogenic factors best differentiate between destructive and non-destructive large fires?
(3) Do these explanatory factors vary among regions?

2. Materials and Methods

2.1. Study Regions

Given previous research that demonstrated regional differences in variable importance for factors explaining the probability of large fires and structure loss [22,58], we performed our analyses separately for three regions in California where structure loss has been extensive. These areas are the northern and southern San Francisco Bay Area ("Bay Area"), the northern Sierra Nevada foothills and mountains ("North Sierra Foothills"), and the southern coastal region ("South Coast"). All three regions are characterized as having Mediterranean climates, with warm to hot, dry summers and wet winters. The only region to receive substantial snowfall is the North Sierra Foothills.

The Bay Area region includes 33,223,500 ha of land to the north and south of the San Francisco—Oakland metropolitan area, which is the second largest metropolitan area in the state (Figure 1). The mean population density for the region is 1.93 people per ha. While the metropolitan region is characterized by expansive high-density urban development, much open space remains in the region. Nevertheless, there has been extensive housing development in recent decades, and 16% of the land was mapped as Wildland Urban Interface as of 2010 [27], with a mean landscape-scale distance to WUI being 3.22 km. The region extends from the coast through the coastal ranges with the border ending at the Central Valley. Much of the vegetation is characterized by oak woodlands and grasslands, forming a mosaic with chaparral and hardwood forests, with montane forests at the highest elevations. The northern part of the region is where the 2017 "wine country" fires occurred, in which nearly 9000 structures were destroyed and 44 people lost their lives (https://www.fire.ca.gov/incidents/2017/) (accessed on 25 August 2022).

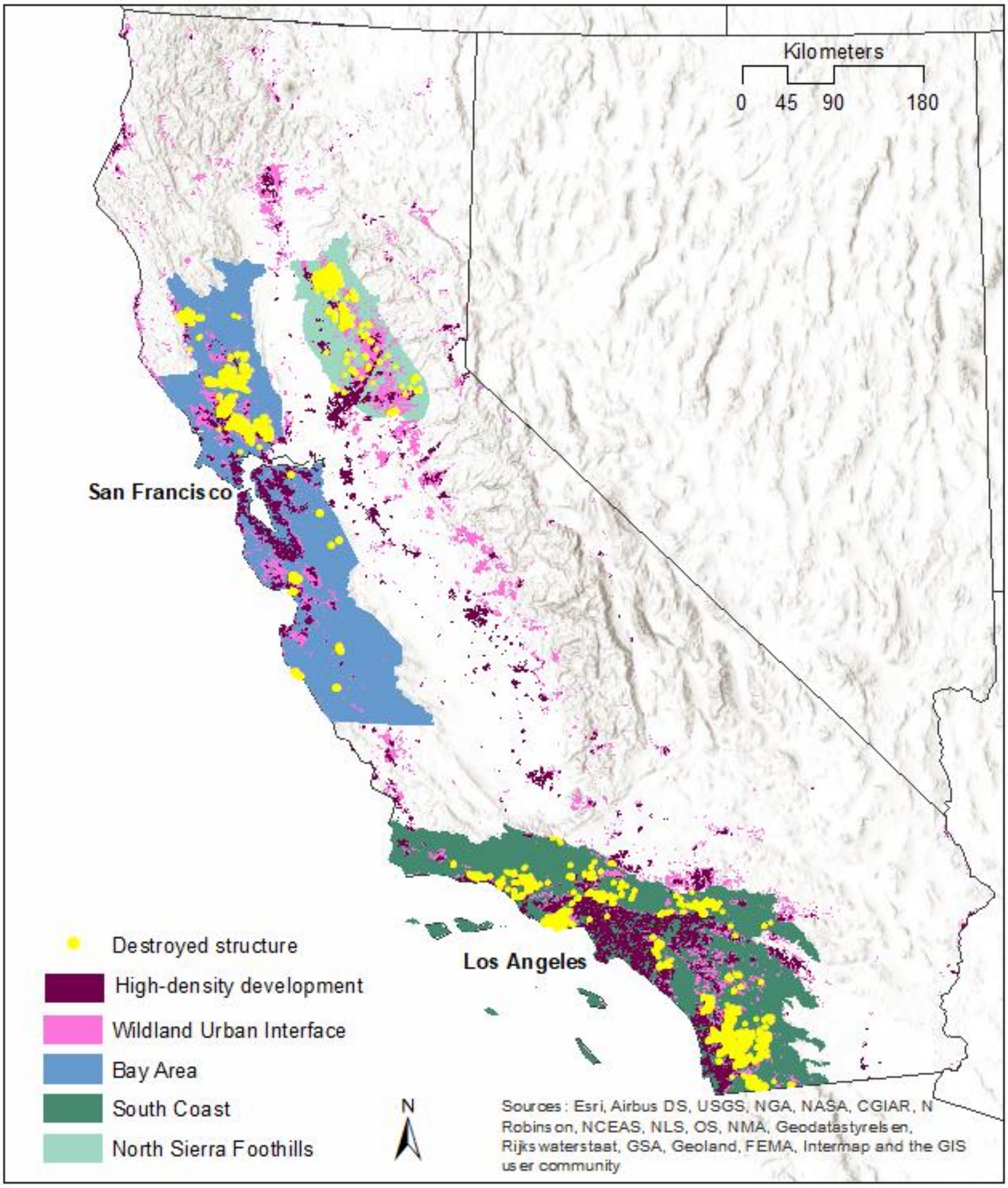

Figure 1. The Bay Area, North Sierra Foothills, and South Coast study regions in California, USA.

The North Sierra Foothills region contains 9,404,800 ha of land spanning the gradient from the central valley on the west to the northern cismontane Sierra Nevada on the east (Figure 1). With a mean of 1.0 people per ha, this study region has the lowest population density, with no major cities within. However, the region has the highest proportion of WUI of the three regions, with 37% area mapped as WUI as of 2010 and an average distance to WUI being 2.01 km. The vegetation is primarily grassland and chaparral at the lowest elevations and transitions eastward and higher in elevation through mixed evergreen forests to pine- and fir-dominated forests, with small areas of sub-alpine forests at the highest elevations. This region has had a growing number of destructive fires in recent decades, with the most notable being the 2018 Camp Fire that destroyed more than 18,000 structures and resulted in 86 lives lost.

The South Coast region is 36,170,100 ha and contains extensive high-density urban development along the coast, including both the Los Angeles and San Diego metropolitan areas. Accordingly, this region also has the highest population density of 4.68 people per ha. Much of the population lives in high-density urban areas. Therefore, although it is the most populous region, it is also the region with longest landscape-scale distance on average to the WUI, at 4.01 km. The proportion of WUI in the region is 18%. Most of the vegetation in the South Coast region is non-forested, with coastal sage and chaparral shrublands interspersed with grassland and oak woodland, although montane conifer forests dominate at the highest elevations. Southern California has a long history of wind-dominated destructive wildfires [54].

2.2. Fire and Structure Loss Data

Our structure loss data consisted of geographical coordinates for the locations of residential buildings destroyed between 2000–2018 and described in previous studies (e.g., [22,58,59]). The structure loss dataset included a combination of digitized points from the visual identification of destroyed structures using pre- and post-fire Google Earth Imagery in addition to points provided via public records request from the Cal Fire Damage INSPection Program (DINS data) (DINS data, https://gis.data.ca.gov/datasets/1b1c428af1f74a8c912f4b5c9e40d51e/about) (accessed on 25 August 2022). In total, the data included 176,690 structures, with 50,516 having been destroyed in a wildfire.

For fire perimeters, we selected and used all fires from 2000–2018 that overlapped our study area boundaries from the digital historical overlapping fire perimeter data from Cal Fire (https://frap.ca.gov/mapping/gis-data/) (accessed on 25 August 2022). After overlaying the fire perimeters with the structure loss data, we counted the number of destroyed structures within and labeled any perimeter that contained at least one structure destroyed as "destructive" and any perimeter with no structures destroyed as "non-destructive" (Table 1).

Table 1. Number of all and large (≥100 ha) destructive and non-destructive fires from 2000–2018 in three California regions.

All Fires: Region	Destructive	Total	Proportion
Bay Area	41	579	0.07
North Sierra Foothills	59	404	0.15
South Coast	59	1475	0.04
Total	159	2458	0.06
Large Fires: Region			
Bay Area	30	180	0.17
North Sierra Foothills	33	89	0.37
South Coast	54	349	0.15
Total	117	618	0.19

In addition to the locations of destroyed structures, we also overlaid and counted the total number of structures within each fire perimeter using the open-access Microsoft Building Footprint dataset (https://www.microsoft.com/en-us/maps/building-footprints) (accessed on 25 August 2022). For each fire, we then quantified the proportion destroyed of the total number of structures within the perimeter.

2.3. Explanatory Variables

To identify characteristics most strongly associated with destructive fires, we evaluated a range of climate, weather, fuel, and anthropogenic variables that could potentially affect fire behavior or fire exposure. These variables we analyzed in the statistical analyses reflected conditions that were present before the fire occurred. We also summarized the size and severity of all fires for descriptive differentiation. For different variable types (i.e., weather, seasonal climate, and human infrastructure), we compared a suite of related variables, described below, and selected the ones for statistical analysis that were uncorrelated ($r < 0.7$) and had the highest bivariate correlation with the percentage of structures burned in the fires (i.e., 0–100).

Our source of weather data was the Gridded Meteorological Dataset (GRIDMET) [60], from which we extracted relative humidity (RH), maximum temperature, 100 and 1000-h fuel moisture, wind velocity, and energy release component (ERC, a fire danger rating index that approximates fuel moisture) for the first day of the fire and for 7 and 30 days prior to the fire. The ERC is a weather-climate buildup index calculated using daily temperature, precipitation, humidity, and other meteorological variables over a fuel model to represent potential fireline intensity [60], with the gridded weather continually updated. Many of these variables were highly correlated, so, using the approach described above, we retained relative humidity, energy release component, and wind velocity for the day of the fire ($r = -0.10$, 0.10, and 0.4, respectively).

For seasonal climate variables, we extracted monthly mean precipitation and monthly mean and maximum temperature from 2.5 arc min PRISM data for every fire perimeter (PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu) (accessed on 25 August 2022), averaged the monthly values for the four seasons (Winter: December–February; Spring: March–May; Summer: June–August; Autumn: September–November) and averaged these values across the area of the fire perimeters. We considered climate variables for all seasons for all fires due to the potential longer-term influence of these variables on fuel conditions at the time of fire. These seasonal values corresponded to the year of or preceding the year of the fire depending on the date of the fire. We also extracted the vapor pressure deficit and mean annual precipitation for the years of and before the fire. After checking for correlations among this group of climate variables, we retained mean autumn precipitation ($r = 0.15$) and mean summer temperature ($r = 0.02$).

For anthropogenic variables, we considered the proximity of fires to roads (which could represent firefighter access) and the Wildland Urban Interface (WUI), which is where wildfires are most likely to destroy structures [27,53]. We analyzed these variables to determine if location of fires relative to human presence influences the likelihood that the fire will become destructive. For the roads, we used the TIGER line Census data (https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html) (accessed on 25 August 2022) to calculate the mean and minimum distance of all cells within fire perimeters to the road. We compared the minimum and mean because the values of these variables could be different in larger fires. Similarly, to assess the proximity of fires to the WUI, we calculated the minimum and mean distance of fire perimeters to Intermix, Interface, and all WUI as mapped in 2010 [61] in addition to the proportion of WUI within fire perimeters. Intermix and Interface WUI vary in terms of the arrangement of housing density and land cover such that intermix WUI refers to the intermingling of structures and vegetation; and interface refers to areas where housing is near large patches of wildland vegetation. Although the mapped WUI was from 2010, and our study included fires up to 2017, we assumed that any changes to the WUI during that time would not significantly influence model results. This is because, once WUI is built, it generally remains in place; and any change would primarily occur in one direction (expansion). The WUI variables we considered were mapped in a binary format (a grid cell was either WUI or it was not WUI), and thus, distance to WUI was either a mean or minimum distance from the cells within a fire perimeter to the closest mapped WUI area. From these variables, we retained distance to all WUI ($r = -0.08$) and distance to roads ($r = -0.07$) as these were the two uncorrelated variables with the strongest relationship with destructive fires.

To account for spatial variation in fuel volume, we extracted and averaged the annual maximum Normalized Difference Vegetation Index (from Landsat TM data at 30 m resolution, https://landsat.gsfc.nasa.gov/article/the-thematic-mapper/ (accessed on 25 August 2022) across fire perimeters for the year of the fire. The annual maximum values account for any variation due to seasonal differences. We also used an average of percentage slope from a 30 m USGS digital elevation model (DEM) (https://www.usgs.gov/3d-elevation-program) (accessed 25 August 2022).

2.4. Analysis

To compare the characteristics of destructive and non-destructive fire events after they had burned, we calculated and compared their final size and severity. Here, fire severity refers to the amount of aboveground biomass consumed by the fire. For fire size, we used a GIS to summarize the area of the spatially explicit fire perimeters. For fire severity, we used USGS Landsat 5 (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LT05_C02_T1_L2), 7 (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LE07_C02_T1_L2), and 8 (https://developers.google.com/earth-engine/datasets/catalog/LANDSAT_LC08_C02_T1_L2) (accessed 25 August 2022). Tier 1 Surface Reflectance to calculate the mean, median, and maximum values of both the delta normalized burn ration (dNBR) and the relativized burn ratio (RBR) for all fire perimeters, and then summarized the burn severity metric that was most highly correlated with destructive wildfires in the analysis. Severity indices were calculated using the closest cloud-free image prior to the ignition data and the closest cloud-free image after the containment data. Others have found the RBR to correspond best with field-based measurements of burn severity [62], and we selected the maximum RBR for this analysis (r = 0.18). To determine whether there were significant differences in burn severity for destructive and non-destructive fires, we checked to ensure a normal distribution of maximum dNBR values for each study region and then ran Welch Two Sample *t*-tests using R Studio.

As most wildfires are small, and structures tend to be destroyed in larger fires, we omitted small fires from the inferential statistical analysis to ensure we were not simply developing models that explain fire size. In other words, we wanted to understand, of the fires that become large, what is the difference between those that result in structure loss and those that do not? Therefore, we used fires $\geq$100 ha for statistical analysis. We created a binary (destructive vs. non-destructive) instead of a continuous (percentage of structures destroyed) response variable because a small percentage of the fires in the dataset were destructive and there was not much variation in the non-zero values of the continuous response.

To explore the relative independent importance of the climate, weather, anthropogenic, and vegetation variables in explaining destructive large fires from non-destructive large fires, we used a hierarchical partitioning multiple regression approach. Hierarchical partitioning iteratively runs through a hierarchy of multiple regression models using all combinations of explanatory variables, calculates the models' goodness of fit, and ultimately produces a measure of variables' ranking of relative importance. We ran the hier.part package in R Studio [63] using destructive versus non-destructive large fires as a binomial response variable and a log likelihood measure of goodness of fit. The output of the model is a percentage distribution of the contribution of the variables' independent effects. The independent contribution is calculated as the improvement in fit for each hierarchical level of multiple regression models including a given variable versus omitting that variable. The improvement in fit is averaged across model hierarchies and results in a metric of percentage of independent contribution. Although hierarchical partitioning may produce a rounding error with more than 9 variables, it is an accurate and robust means of establishing the ranking of variable importance with nine or fewer variables [64], and we used 9 variables in our models.

We also created classification trees [65] to assess and visualize the relative influence of variables in a multivariate framework for the three regions. Classification trees use an iterative clustering algorithm to recursively partition a dataset into a hierarchy of relatively homogenous classes that provide the strongest fit to the binary response (i.e., destructive versus non-destructive fires). The algorithm sorts data according to decision rules that split variables according to thresholds that best differentiate the two classes in the response variable. The graphical output displays the most important variables are at the top of tree, with further splits of the data branching out according to their importance. Only the variables that most effectively split the data are retained in the tree. Thus, classification trees intuitively delineate interactions among variables and provide a clear visualization of how the data are structured. To develop and plot the trees we used r.part and rpart.plot packages in R Studio [63] To assess how well the classification trees fit the training data, we calculated the area under the curve for receiving operating characteristic (ROC) plots [66] using the ROCR package in R Studio [63].

3. Results

Overall, 159 out of 2458 (6%) fires overlapping the study boundaries from 2000–2018 had at least 1 structure destroyed. The Bay Area had 41 destructive fires; the Sierra Nevada had 59; and Southern California had 59 (Table 1). When accounting for all fires in the database, the destructive fires were larger than the non-destructive fires by at least an order of magnitude (Table 2), with most area burned in summer in the Bay Area, autumn in the North Sierra Foothills, and winter in Southern California (Figure 2). When considered across the state, however, most of the area burned in destructive fires occurred in the autumn (Figure 2).

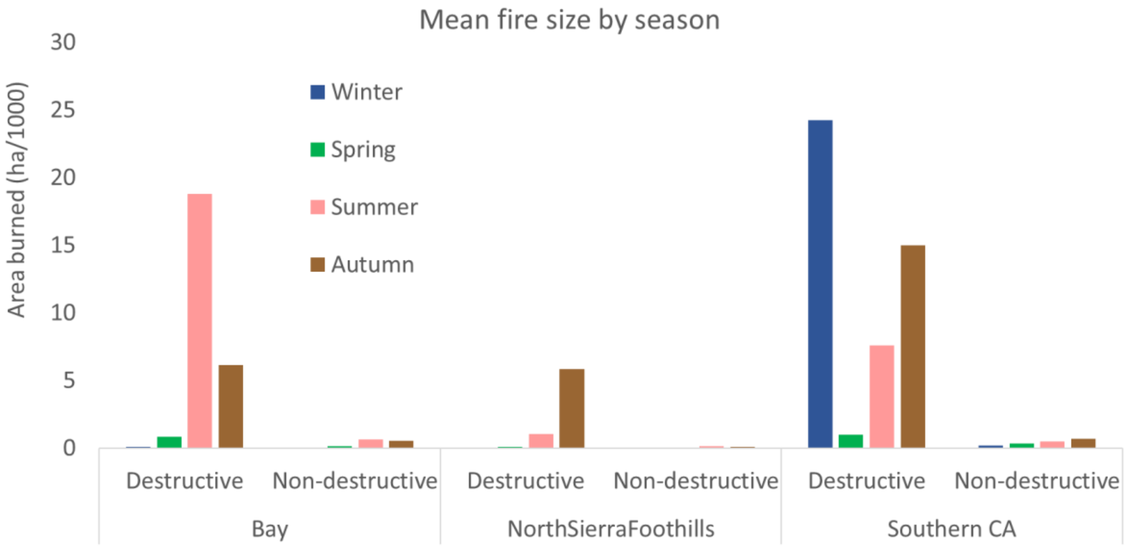

Figure 2. Mean fire size by season for destructive and non-destructive wildfires in three California regions and statewide from 2000–2018.

Table 2. Mean and median fire size (ha) for all (n = 2458) destructive and non-destructive fires from 2000–2018 in three California regions.

	Mean Fire Size		Median Fire Size	
Region	**Destructive**	**Non-Destructive**	**Destructive**	**Non-Destructive**
Bay Area	11,289	531	1349	29
North Sierra Foothills	2439	96	145	16
South Coast	12,551	484	3537	14

Although destructive fires were generally much larger than non-destructive fires, there were 42 destructive fires smaller than 100 ha (2%), with 15 destructive fires smaller than 10 ha. After factoring out small fires, there were 618 large fires ≥100 ha (25% of the total number of fires in the dataset). Of these, 117 were destructive, or, 19% of the fires (Table 1).

Eight of the total number of fires had more than 1000 structures destroyed, with the single largest number of structures lost (n = 19,568) in the Camp Fire in the North Sierra Foothills. The rest of the fires with ≥1000 structures lost were in the Bay Area (n = 3) and Southern California (n = 4). There were 28 fires with more than 100 structures lost, but most destructive fires (n = 92) had fewer than 10 structures lost. Relative to the total number of structures within fire perimeter boundaries, this translates into a relatively low overall average percentage of structures destroyed in destructive fires.

In all three regions, the destructive fires burned at a higher maximum severity than the non-destructive fires (Figure 3). The t-tests showed that the difference was significant for the Bay Area ($p = 0.001$), the North Sierra Foothills ($p = 0.02$), and for Southern California ($p < 0.001$).

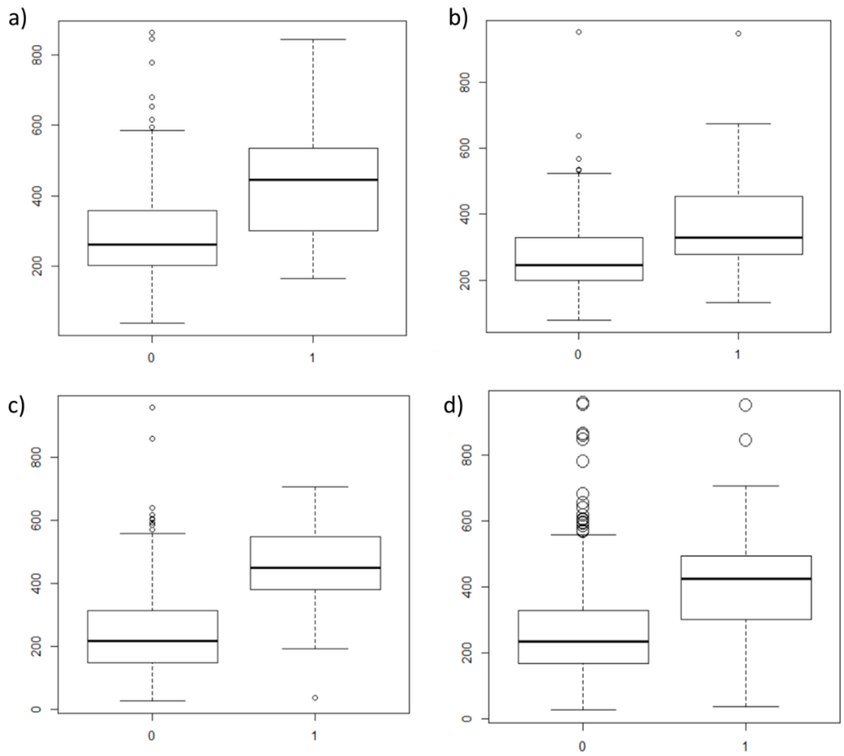

Figure 3. Mean burn severity (maximum dNBR) in non-destructive (0) and destructive (1) wildfires in (**a**) the Bay area (**b**) the North Sierra Foothills (**c**) Southern California, and (**d**) Statewide for all wildfires from 2000–2018. The boxplot depicts the minimum, maximum, and interquartile range (25th to 75th percentile), the median, and outliers displayed as circles.

The differences between destructive and non-destructive fires for the fire weather variables were consistent for all three regions; the relative humidity was lower, the ERC was higher, and the winds were faster for destructive fires (Table 3). The summer temperature was higher in destructive fires for the Bay Area and the South Coast, but it was lower for destructive fires in the North Sierra Foothills. In all regions, autumn precipitation was higher for destructive fires. The maximum NDVI in the fire years was higher for destructive fires in the Bay Area and the South Coast, and it was the same for both destructive and non-destructive fires in the North Sierra Foothills. For all three regions, destructive fires had shorter distances to roads and the WUI than non-destructive fires.

For the hierarchical partitioning results, showing the relative independent contribution of the explanatory variables, distance to the WUI was by far the most important variable for the two northern study regions, the Bay Area and the North Sierra Foothills (Figure 4). In the Bay Area, relative humidity was the second most important variable, with the other variables contributing less than 10% of the relative importance. The second most important variable in the North Sierra Foothills was ERC, but it was not much more than the other variables, each of which contributed less than 5% of the relative importance. In the South Coast region, wind velocity was the most important variable, followed by distance to roads, distance to WUI, and autumn precipitation, with the rest of the variables contributing only a minor amount.

Table 3. Mean values for explanatory variables in models distinguishing destructive and non-destructive large wildfires in three California regions.

	Bay		North Sierra Foothills		South Coast	
	Destructive	**Non-Destructive**	**Destructive**	**Non-Destructive**	**Destructive**	**Non-Destructive**
Relative humidity(%)	18.7	25.3	17.9	20.6	16.7	23.0
ERC (index)	66.7	57.9	74.0	69.4	69.9	61.9
Wind (m/s)	3.8	3.1	3.5	3.2	8.2	7.7
Summer temp (C)	19.8	19.1	21.8	22.1	21.7	19.1
Autumn precip (mm)	99.4	93.8	157.7	142.2	52.7	42.1
NDVI (index)	0.7	0.7	0.7	0.7	0.5	0.5
Slope (degrees)	17.1	13.8	11.3	9.0	16.9	13.7
Distance roads (m)	40.8	89.1	21.6	95.8	17.8	100.5
Distance WUI (m)	2.0	2.3	0.7	1.3	0.6	1.0

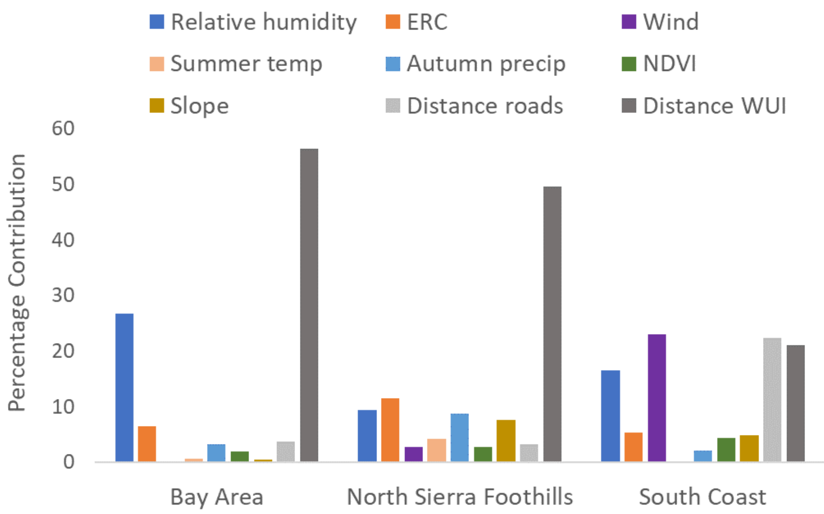

Figure 4. Relative independent variable importance explaining the difference between destructive and non-destructive wildfires ≥100 ha for three California regions from 2000–2018. Variables account for: weather (relative humidity, energy release component (ERC), and wind velocity) on the date that fires started, seasonal climate (summer temperature (summer temp), autumn precipitation (autumn precip, vegetation productivity (normalized difference vegetation index (NDVI) in the year before the fire, slope, distance to roads, and distance to the Wildland Urban Interface (WUI) in the year 2000.

In a multivariate framework, the distance to the WUI was again the most important variable for the two northern regions (Figures 5 and 6), although the thresholds separating destructive from non-destructive fires was different, with a longer-distance threshold for the Bay Area. In the Bay Area, relative humidity was the second most important split of the data, followed by NDVI on the day of the fire, slope, and wind velocity (Figure 5). No other variables were retained in the tree, and the AUC for the tree was 0.91. For the North Sierra Foothills, seasonal climate–autumn precipitation, followed by summer temperature, were the next most important splits of the data, with ERC being the third most important variable and no other variables retained for the tree (Figure 6). The AUC on training data for the North Sierra Foothills tree was 0.85. In Southern California, wind velocity on the day the fire started was the most important variable distinguishing destructive from non-destructive fires in a multivariate framework (Figure 7). The only other two splits and variables in the tree were relative humidity followed by NDVI on the day of the variable. The AUC was 0.66.

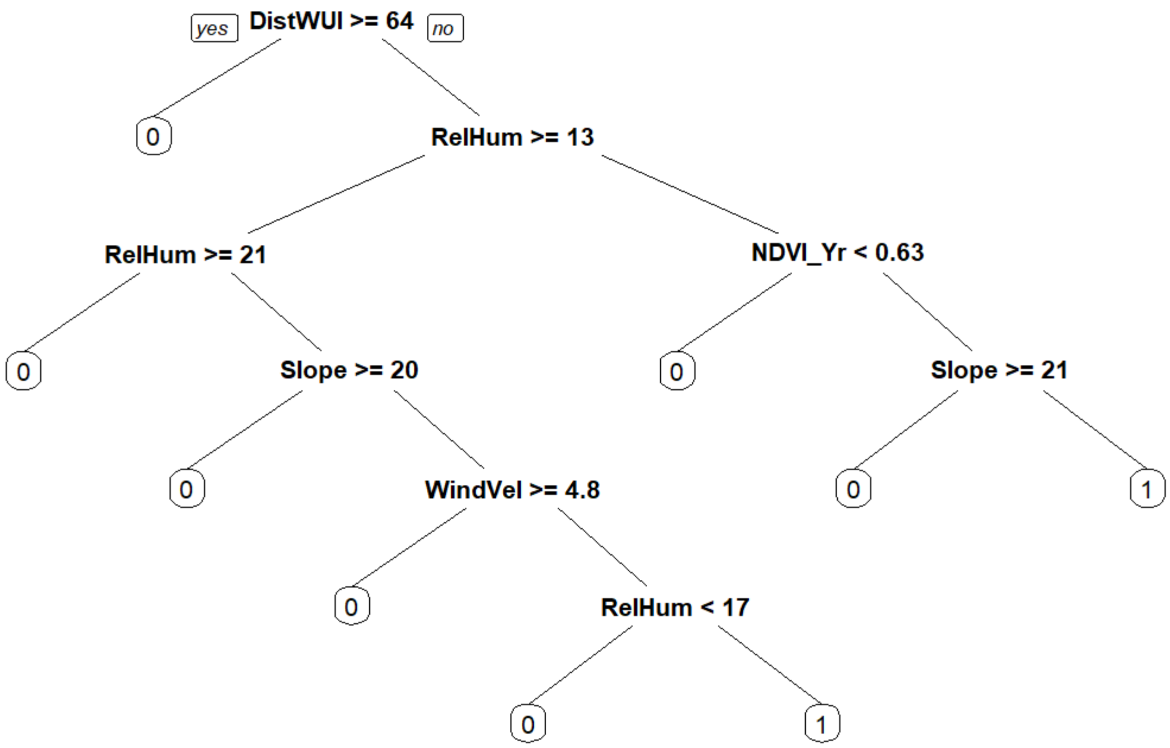

Figure 5. Classification tree explaining the factors differentiating destructive (1) and non-destructive (0) wildfires ≥100 ha fr.om 2000–2018 in the Bay Area of California.

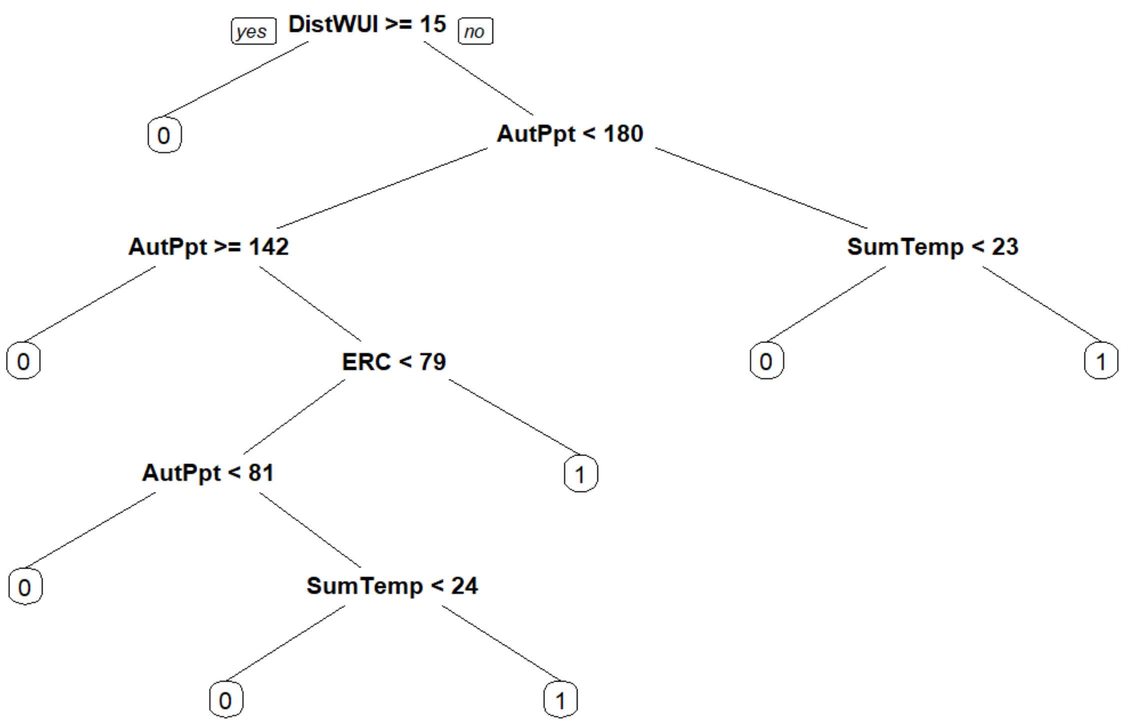

Figure 6. Classification tree explaining the factors differentiating destructive (1) and non-destructive (0) wildfires ≥100 ha from 2000–2018 in the North Sierra Foothills of California.

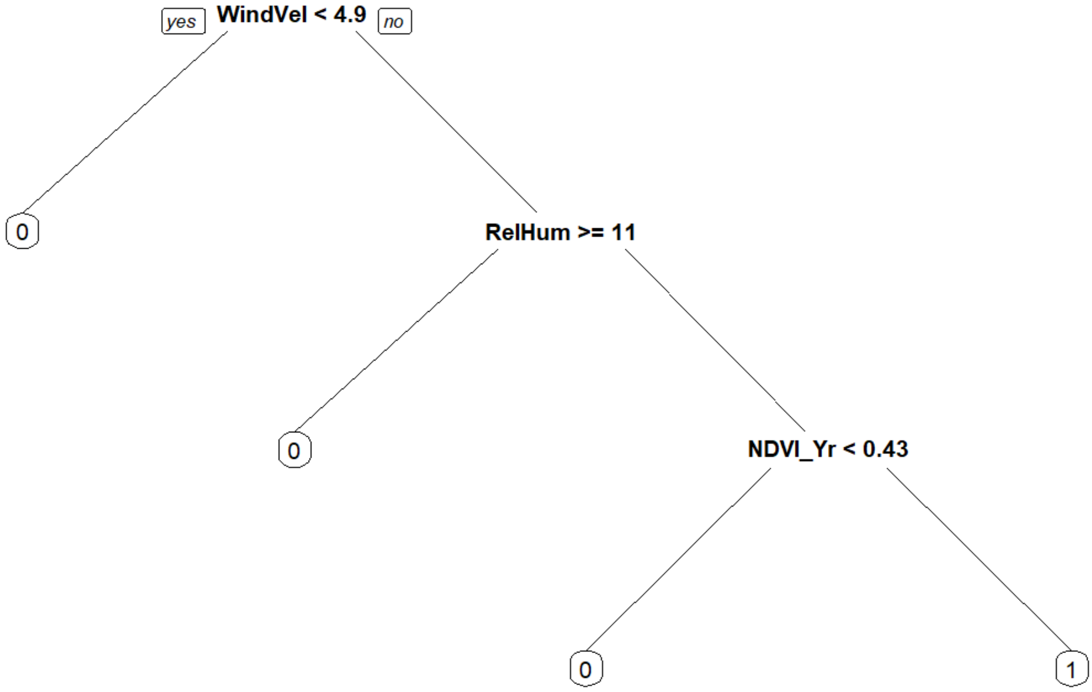

Figure 7. Classification tree explaining the factors differentiating destructive (1) and non-destructive (0) wildfires ≥100 ha from 2000–2018 in Southern California.

4. Discussion

Not surprisingly, fires that resulted in structure loss were significantly larger and burned at higher severity than fires that did not result in structure loss. In general, most fires become large during severe fire-weather conditions, with strong winds or low fuel moisture [67], which are also the conditions that increase fire suppression difficulty [68]. Thus, it makes sense that structure loss often occurs in large fires that are difficult to control. In terms of the factors distinguishing large fires that become destructive versus large fires that do not, there were different combinations of short-term weather, seasonal climate, slope, and proximity to human infrastructure that were important in the three regions, with the two northern regions being most similar. In the two northern regions, proximity to the WUI was overwhelmingly the most important factor; but in Southern California, wind velocity on the day of the fire was most important.

While it may seem obvious that destructive fires were most likely to occur close to the WUI, fire danger is typically characterized by fuel and meteorological conditions rather than location. The strong importance of proximity to WUI supports the notion that, once fires get large, structure destruction is as much or more about structure exposure than differences attributable to the fire itself. In other words, for the two northern regions, characteristics of large fires were relatively similar—and the ones most likely to destroy structures were those in which structures were in closer proximity to the fire. In a broader-scale global study, Bowman et al. [32] also found that disastrous extreme fire events were most common in areas that had intermediate population density (>1 and <100 humans per km^2), which is another way to consider exposure. Differences between exposure and sensitivity are often highlighted in hazard research because exposure is the first and necessary condition to be met before damage or destruction occurs [26,69,70].

Although Southern California is by far the most populous of the three regions, much of the population lives in high-density cities like Los Angeles and San Diego. Thus, surprisingly, it is the region with the longest overall mean distance to the WUI. Nevertheless, although distance from the fire to the WUI was not the top factor as it was in the other two regions, it was the third most important variable in the hierarchical partitioning analysis.

Thus, exposure here is also a significant determinant of why fires become destructive. This is consistent with other studies showing that housing arrangement and location, namely low housing density, are the most important factors influencing structure loss in Southern California [71–73], as they are elsewhere in the state [21].

Low- to intermediate-density housing development exposes structures to more surrounding wildland vegetation, and this is one reason that land use planning could be one of the most effective long-term strategies to reduce the likelihood that future fires become more destructive [74–76]. One caveat to this is that, once a development is exposed to and experiences a wildfire, the housing density relationship may cross a threshold in which the direction of influence flips—and then higher density is a bigger risk factor due to the potential for structure-to-structure ignition [77].

Instead of distance to the WUI, high wind velocity on the day of fire ignition was the top-ranking factor distinguishing destructive and non-destructive fires in Southern California. This is not surprising, as wind-driven fires are generally implicated as the most destructive [29,32,78], especially in Southern California where extreme wind conditions have long been associated with structure loss [29,79]. Hot, dry, strong, offshore foehn winds, notably Santa Ana winds, originate from eastern deserts every year, and their frequency increases during the autumn and winter when fuel moisture is driest after the long summer drought, characteristic of the Mediterranean climate. This partly explains why the most area burned in Southern California occurs in winter and autumn (Figure 2).

When an ignition occurs during one of these Santa Ana wind events, wildfire behavior readily becomes extreme, spreading rapidly, and casting embers kilometers from the fire front. These conditions are particularly dangerous and difficult to defend, limiting firefighter access to strategic locations for suppression [80]. Many destructive fires in northern areas of California, particularly in recent years, have also been wind-driven [81,82]. However, there may be less variability in the wind conditions between large fires that are destructive or not in those regions, which may explain why it was less important there. Another potential reason that wind was less important in the north is that we only accounted for wind on the first day of the fire instead of the entire fire duration. This may have resulted in an underestimation of the importance of wind. Nevertheless, wind on the first day of the fire is clearly of critical importance in Southern California.

In the classification tree for Southern California, the second most important variable was relative humidity, which regulates fuel moisture and promotes ignitability. This is consistent with findings by Jin et al., [83] who found that low relative humidity is strongly associated with Santa Ana wind fire spread and size, and thus potentially with suppression difficulty. Relative humidity could potentially increase home flammability as well. The combination of winds and low relative humidity may be particularly problematical in Southern California owing to the large human population and potential for fire ignition. Humans cause the vast majority of ignitions in this region (and across the state) [41], and recent work has shown that number of ignitions is the strongest variable explaining area burned in Santa Ana wind fires, more than climate or weather 51. Human-caused fires in general are more likely to result in extreme fire behavior than lightning-caused fires [52].

In this study, we only considered the wind velocity on the first day of the fire, which we assumed to be the most destructive day. Given that Santa Ana events often occur over several days, the wind on the first day of the fire may also be a strong indicator of wind on the immediately following days. Nevertheless, we recognize that by only considering this one wind variable we may have missed the role of wind on the following days of the fires. We also did not consider wind direction here, which could be a clear predictor of fire danger as most of the foehn winds are northeasterly winds.

5. Conclusions

This study illustrates the multivariate and geographically varying factors that combine to describe why fires become destructive. The importance of multiple factors in different regions confirms that wildfire initiation and propagation are complex processes driven by a suite of bottom-up (e.g., topography or NDVI) and top-down (e.g., climate or distance to WUI) factors with varying degrees of spatial (e.g., distance and location) and temporal (e.g., daily weather and seasonal climate) dependency [84,85]. While this complexity is a challenge for management and decision-making, and for making future fire projections [86], the consistent importance of weather on the day of ignition and proximity to WUI can inform decision-making. Land use planning to reduce exposure of new housing to weather-driven wildfires could help prevent future losses. In addition, given the importance of ignitions and ignition location relative to wind-driven fires in particular, targeted ignition prevention programs could reduce the occurrence and frequency of wildfires with potential to become destructive. Future work focused on detailed case studies and fire behavior throughout the course of destructive fire events could further our understanding of when and where to focus planning efforts.

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