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Exploring urban vegetation type and defensible space's role in building loss during wildfire-driven events in California

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HIGHLIGHTS

- Few studies on urban vegetation type's role on building loss/survival during fires.
- Mapped fire damaged buildings and parcel-scale vegetation types using eCognition.
- 2 models predicted building loss/survival across 3 buffer distances from buildings.
- Vegetation type-moisture, ground cover, building density; influential predictors.
- High tree moisture and bare ground cover near homes; predicted building survival.

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ABSTRACT

The role of building characteristics and survival during wildfires are well studied. Less so is the role of urban vegetation type, condition, and location on building loss in fire events. We mapped and statistically modeled parcel-scale urban vegetation characteristics across different Defensible Space Buffers (DSBs) and their role in predicting building loss in shrub and forest dominated urban ecosystems. Using 3.0 m resolution PlanetScope imagery, geospatial data, and eCognition we mapped parcel-scale vegetation types and building characteristics in fire affected neighborhoods in Ventura and Paradise, California US. Classification and Regression Trees predicted building loss according to three different DSBs in two different ecoregions. An urban-chaparral model predicted higher bare ground cover and higher moisture content trees were significant predictors of building survival in DSBs 0–2 m from buildings. While in DSBs 10–20 m from buildings, percent bare ground, distance to herbaceous, building density, and tree distance were predictors of building loss. The urban-forest model predicted percent bare ground, distance to bare ground and herbaceous cover were significant predictors of buildings loss, while percent overhanging tree cover was less influential in predicting in building loss in DSBs less than 2 m. In DSBs 2–10 m from buildings, low shrub and tree moisture, and building densities were the most important predictors of building loss; while distance to scattered trees and building density were significant predictors in DSBs 10–20 m from buildings. Results can be used to understand the tradeoffs between vegetation-related benefits and fire hazard and for developing home insurance and municipal ordinance requirements.

1. Introduction

Wildfire driven urban fires are increasingly affecting ecosystems and human settlements and are now an emerging extreme disturbance event spanning multiple scales with increasing fire severity, and costly economic, social, and environmental impacts (Bowman et al., 2017; Calkin et al., 2024; Moritz et al., 2014). In the United States (US) alone, communities in California are experiencing complex land use decisions, socio-political issues, and financial burdens that are being exacerbated by changing climates, and urbanization (Calkin et al., 2023; Modaresi, et al., 2023). Elsewhere, urban ecosystems in Australia (Cruz et al., 2012; Gibbons et al., 2018), Canada (Erni et al., 2021), Southern Europe (Elia et al., 2020; Mancini et al., 2018), Chile (Aguirre et al., 2024) and even Hawaii (US) are now experiencing these impacts as well increased

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loss of human lives.

Increased urban development in and near wildland areas or the Wildland-Urban Interface (WUI) has led to increased ignition sources and wildfire risk (Kramer et al., 2019; Syphard et al., 2017b). Similarly, WUI and adjacent urban ecosystems are also experiencing increased demographic change, population increases, conversion of habitats, and increasing fire impacts (Calkin et al. 2024; Yadav et al., 2023). As both land use and climate change extend wildfire seasons and exacerbates wildfire hazard, increased land management practices, regulatory urban planning policies, and building construction guidelines are being established (Elia et al., 2024; Goss et al., 2020; Halofsky et al., 2020). Indeed, building construction practices are a documented measure for reducing building loss probability (Knapp et al., 2021; Syphard et al., 2021) as are WUI land management practices for mitigating wildfire risk (Cohen and Stratton, 2003). However, less is known about the role of local-scale urban vegetation characteristics in building loss during urban fire events in highly urbanized and populated urban areas (Mancini et al., 2018; Thomas et al., 2022).

More specifically, studies on the role of wildfire in building loss and survival have mostly focused on building characteristics in the WUI and to a lesser degree on urban vegetation type and amount in the Home Ignition Zone or Defensible Space Buffers (hereafter) around homes (U. S. FEMA, 2023; Valachovic et al., 2021). Several studies have documented how building codes requiring construction practices and fire-resistant materials as well as the establishment of defensible space reduce building loss during fire events (Ackley, 2020; Mockrin et al., 2023; Syphard et al., 2021). Plant flammability and forest vegetation cover in these home ignition zones have also been reported to influence structure survival during wildfires (Cappelluti et al., 2024; Kramer et al. 2019). As such, percent tree cover, Normalized Difference Vegetation Index (NDVI), and distance to buildings using remotely sensed data (e.g., LANDSAT 30 m, aerial photography) are regularly used to correlate basic vegetation cover metrics and building loss during wildfires (Knapp et al., 2021; Syphard et al., 2014). These same vegetation cover and distance metrics have also been used to explore the role of Defensible Space in reducing building loss during fire events in the WUI (Gibbons et al., 2012; Troy et al., 2022).

However, the results from these studies have been mixed in terms of the effectiveness of these Defensible Space Buffer (DSB) practices (Penman et al., 2019; Syphard et al., 2014). Bar-Massada et al. (2011), Braziunas et al. (2021) and Cohen and Stratton (2003) studied overall vegetation cover and its role as fuel for wildfires and how certain building practices enhance the survivability of buildings (Hakes et al., 2017; Quarles et al., 2010). In fact, most of the above literature has been done in WUI or more rural contexts and has focused on building codes and construction practices in reducing building loss during fires (Gibbons et al., 2018; Suzuki et al., 2014). Conversely, there are very few studies focused on urban ecosystems or vegetation around urban homes, specifically: vegetation structure and composition, moisture levels, overall health and condition, building densities, and the distances of these different fuel types and their role in the loss of homes during catastrophic urban fire events (Aguirre et al., 2024; Chen & McAneney, 2004; Thomas et al., 2022).

In communities such as those in California USA, municipal codes and insurance companies are regularly requiring that these WUI and wildland focused DSB practices be implemented in more urbanized, highly populated, highly impervious residential and commercial areas (Knapp et al, 2021; Moritz et al., 2014; Syphard et al., 2021). Since urban fires are now increasingly affecting highly urbanized ecosystems throughout the globe, more information is needed to better understand the role of urban vegetation/fuels around buildings and the effectiveness of defensible space zones and their interactions with building damage during fire events (Aguirre et al., 2024; Calkin et al, 2024; Mockrin et al., 2023).

Much of the previous literature documents how building and construction-related variables are more influential than vegetation cover classes in building loss and survival during wildfire events. However, there are few studies examining the role of urban vegetation characteristics and DSBs on building loss using available high resolution spatial data and quantitative analyses. Therefore, we hypothesize that beyond vegetation land cover classes, finer-scale urban vegetation: types, moisture, and location relative to homes are also influencing factors behind building loss during fire events in more highly populated urban areas. Accordingly, the aim of this study is to better understand how parcel-scale urban vegetation characteristics across different DSBs influence building loss in shrub and forest dominated urban areas in California, USA. Specifically, our objectives are to first, characterize fine-scale urban vegetation types, densities, and moisture levels around buildings in two disparate fire-affected neighborhoods in different ecoregions. Second, we statistically analyze how vegetation type, densities, moisture, location, and building characteristics across DSBs, influenced building loss during urban fire events. Findings from objectives 1 and 2 will then be used to discuss the role of vegetation types, densities, location, and moisture in meeting defensible space and wildfire mitigation objectives in fire-prone urban ecosystems.

2. Methods

2.1. Study area

Our study areas are two different fire-affected urban ecosystems in two different ecoregions in California USA according to Bailey (1983): the Thomas Fire affected City of Ventura (December 4, 2017 – January 12, 2018) and the Camp Fire affected Town of Paradise (November 8–26, 2018). We define urban based on Yadav et al.'s (2023) urban census tract approach that identifies these communities as having more than 2500 inhabitants and where higher density residential, commercial, and transportation land cover types predominate. Ventura is representative of communities in southern California's coastal sage-chaparral ecoregions and approximately 345 urban hectares were fire-affected. Paradise is representative of inland, northern California communities in the Sierra Nevada ecoregion and about 4678 urban hectares were fire-affected. The Thomas Fire destroyed 1,643 structures and claimed two lives (Kolden and Henson, 2019) while the Camp Fire, resulted in 85 fatalities and the loss of over 18,000 structures (Maranghides et al., 2021).

The vegetation and landscapes found in the two fire affected communities are representative of two common fire-prone urban ecosystems in California with respect to urban land use-covers, vegetation types, and composition (Escobedo et al., 2024; Mockrin et al., 2023). Ventura is characterized by a Mediterranean climate with peri-urban vegetation dominated by native chaparral shrub species and afforested trees and landscaping vegetation in the urban land use covers. Among the most common types of urban vegetation are *Eucalyptus* spp., *Querus* spp., and *Cupressus spp*. trees, as well as ornamental shrubs (e.g., *Heteromeles arbutifolia*), forbs (e.g., *Eriogonum* spp.), and turf grasses. Accordingly, Ventura will be used to characterize highly populated afforested urban-chaparral ecosystems hereafter. Fire affected neighborhoods in Paradise were characterized by a Mediterranean climate and vegetation commonly found throughout the Sierra Nevada ecoregion and were predominantly *Pinus* spp., *Abies* spp., and *Calocedrus* spp. forests with deciduous trees in riparian areas and some *Quercus* spp. woodlands and shrublands. Such ecosystems are forested but were subsequently urbanized but have a forest structure like adjacent WUI areas. As such, Paradise will be used to characterize urban-forest ecosystems in our analysis. Both urban neighborhoods experienced easterly wind events and are located in broad, nearly level to hilly ridges, but are interspersed with steep to very steep canyons or hill sides.

2.2. Urban neighborhood delineation

Two fire affected neighborhoods in Ventura and Paradise were delineated based on urban land use-cover classes derived from National Land Cover Data 2016 (https://www.mrlc.gov/data; Wickham, et al., 2021) and Google Earth Images during 2017–2018. The urban neighborhoods were delineated based on spatial datasets available from the Ventura and Paradise municipal websites (Fig. 1) and fire perimeter data described later in Section 2.2.1.

2.2.1. Remote sensing, Wildfire, and building Damage data

We developed a high spatial resolution (3.0 m), parcel-scale map of the different vegetation types near fire-affected buildings using PlanetScope satellite data (https://developers.planet.com/docs/data/planetscope/; Fig. 1-S). PlanetScope data are available in basic and ortho geometry types and visual and analytic radiometry products. Accordingly, for our urban vegetation types, we used ortho analytic 4 band surface reflectance scenes in a single-frame image capture with additional post processing, scene-based framing, and cartographic projection. The 4 bands used were: Blue (455––515 nm), Green (500––590 nm), Red (590––670 nm) and Near Infrared (780––860 nm) and data had a daily revisit time at nadir. The available scenes were atmospherically corrected and radiometrically interpreted 12-bit images. We used a cloud-free image from December 4, 2017 for Ventura and November 7, 2018 for Paradise.

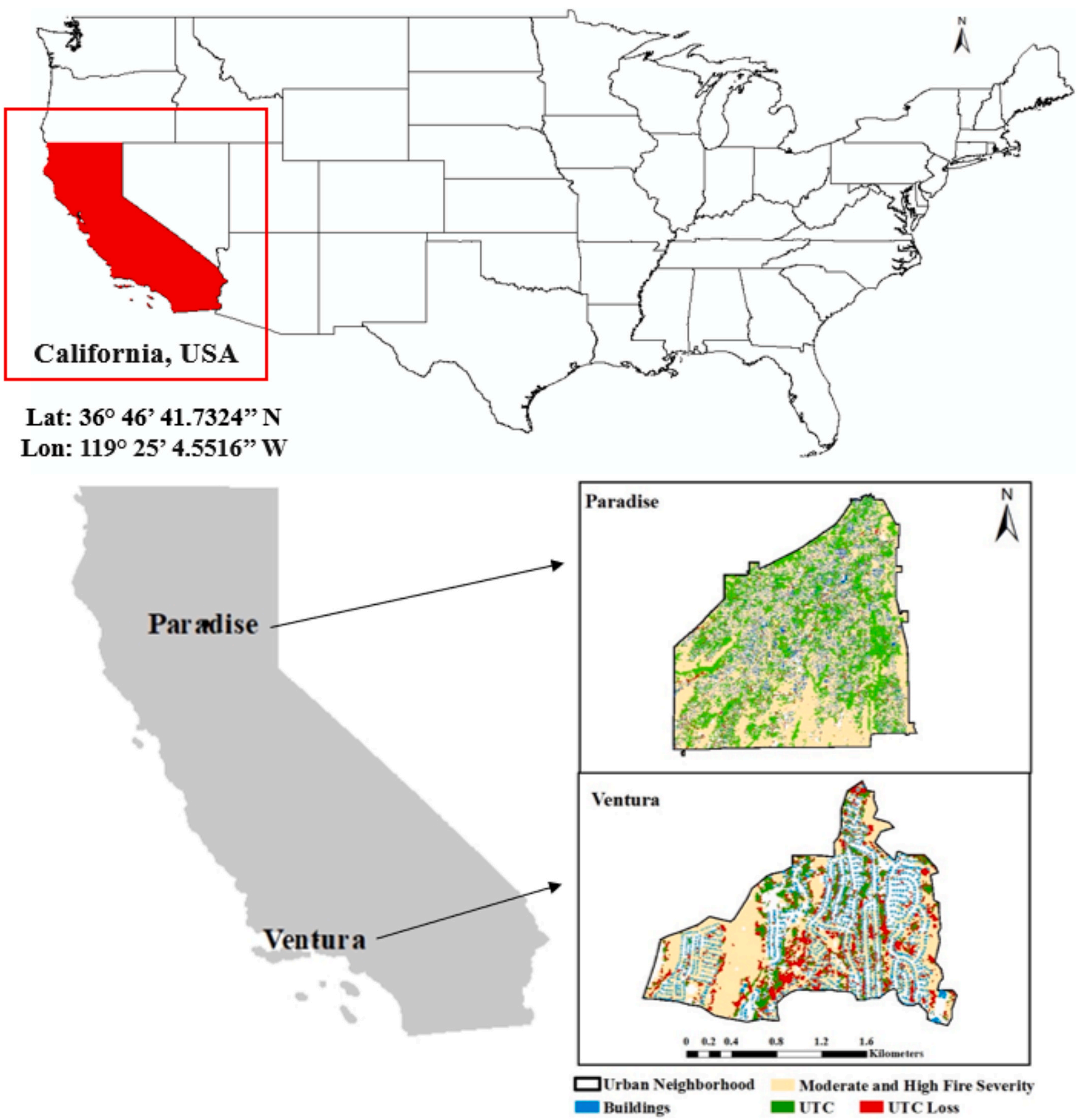

Fig. 1. Fire affected urban neighborhood study areas in Paradise and Ventura, California, USA. These two selected urban neighborhoods also exhibit fire severity, Urban Tree Cover (UTC), and UTC loss from pre- to post-fire.

Fire perimeters were mapped using Cal Fire's Fire and Resource Assessment Program (FRAP) data of historical fire perimeters for the Thomas (2017) and Camp (2018) fires (https://www.fire.ca.gov/what-we-do/fire-resource-assessment-program/fire-perimeters). The FRAP data is one of the most complete digital records of fire perimeters in California and is compiled from Cal Fire units as well as from cooperating land and fire management organizations in California.

Individual fire affected buildings in the study area were mapped using the Microsoft Building footprint data (https://github.com/Microsoft/USBuildingFootprints). The building layer was downloaded as a GeoJSON and converted to a shape file format using Python tools (Fig. 2). Damaged buildings were then identified using the 2020 wildfire building Damage Inspection Schema (DINS) data from the CAL FIRE Office of the State Fire Marshal that assesses and records structure damage during wildland fire incidents (https://gis.data.ca.gov/datasets/1b1c428af1f74a8c912f4b5c9e40d51e/about). The damage classes used in this analysis and their descriptions are presented in the Table 1 and are based on literature such as Knapp et al. (2021), Syphard et al. (2014), Gibbons et al. (2012) and Troy et al. (2022) that identifies building characteristics that are corelated to building loss during wildfires.

We accounted for both vegetation and building characteristics as dependent variables in our urban-forest model that analyzed building destruction and survival for Paradise only. Based on Knapp et al. (2021), we grouped the year a home was built into 3 classes: pre-1997, 1997–2007, and 2008–2018, the latter two time periods are related to periods before and after implementation of California's Building Code Chapter 7A, requiring fire resistant building construction measures. We also accounted for the exterior surface of roof construction materials per Knapp et al., (2021; e.g., metal, asphalt, tile, and concrete). Detailed building data (i.e., Year built and exterior surface material) were not available from the DINS data for Ventura, however we developed a more simplified urban-chaparral model for Ventura that only focused on urban vegetation characteristics and their influence on building destruction.

2.2.2. Defensible space buffers surrounding fire-affected buildings

Our review of the wildfire and building loss studies in Section 1, shows that building loss and survivability are highly correlated with building characteristics and surrounding vegetation cover within 200 feet from the building. Accordingly, this area referred to as DSBs is generally divided into three zones that are referred to as: immediate or Zone 1 (0–2 m), intermediate or Zone 2 (2–10 m), and extended or Zone 3 (10–30 m). These zones were delineated bases on criteria from the National Fire Protection Association (NFPA; https://www.nfpa.org/education-and-research/wildfire/preparing-homes-for-wildfire) to characterize parcel-scale building characteristics and adjacent vegetation types and their characteristics (Table 1). We delineated the three DSBs around building footprints using sequential rectangular polygons with the 'Buffer' spatial analyst tool in ArcGIS Pro version 3.2 (Fig. 2). This method allowed us to systematically map and define these buffers based on their proximity to each building edge in our two study areas. These buffers or zones are regularly used by fire and urban planning entities in North America, Australia, southern Europe and elsewhere as guidelines and ordinances for wildfire risk management (Penman et al., 2019; Syphard et al., 2021).

Table 1
Building characteristics and variables used in the parcel-based building-urban vegetation analysis.

Building Characteristics	Description
Damage classes	1–9 %, Affected Damage; 10–25 %, Minor Damage, 26–50 %: Major Damage, 51–100 %: Destroyed; No Damage
Exterior Surface: Roof Construction Material	Asphalt, Metal, Concrete, Tile
Year Built	Before 1900, 1900–2008, After 2008*

* California Building Code Chapter 7A went into effect in 2008, requiring fire resistance measures including: exterior construction materials used for roof coverings, vents, exterior walls, and decks.
Source: Cal Fire Damage Inspection data)

2.2.3. Data processing and urban vegetation classification

The orthorectified and radiometrically corrected surface reflectance 4-band PlanetScope pre-fire, mosaicked scenes (Fig. 4-A) were extracted and clipped to fire perimeters in both study areas. The pre-fire data were mosaicked using ERDAS Imagine software (Fig. 3, Step- A) to load study area data for use with eCognition. We used eCognition for our object-based classification as well as the spectral information, shape, compactness and other parameters to extract objects (Estoque et al., 2015; Wojtaszek et al., 2021). Specifically, our vegetation type maps for the two-fire affected urban neighborhoods were developed using pre-fire imagery (Fig. 2-S) and the eCognition software version 10.3 (Fig. 3-B). For specific methods related to the work flow that was used to map parcel-scale urban vegetation types (Fig. 3-C-D) and the classification scheme for the urban vegetation (i.e., Shrubs, Trees, Scattered trees, herbaceous) and non-vegetation types used in both our study sites (Fig. 2-S), refer to **Supplementary Methods** (**Sup. Mat. 1**). Non-

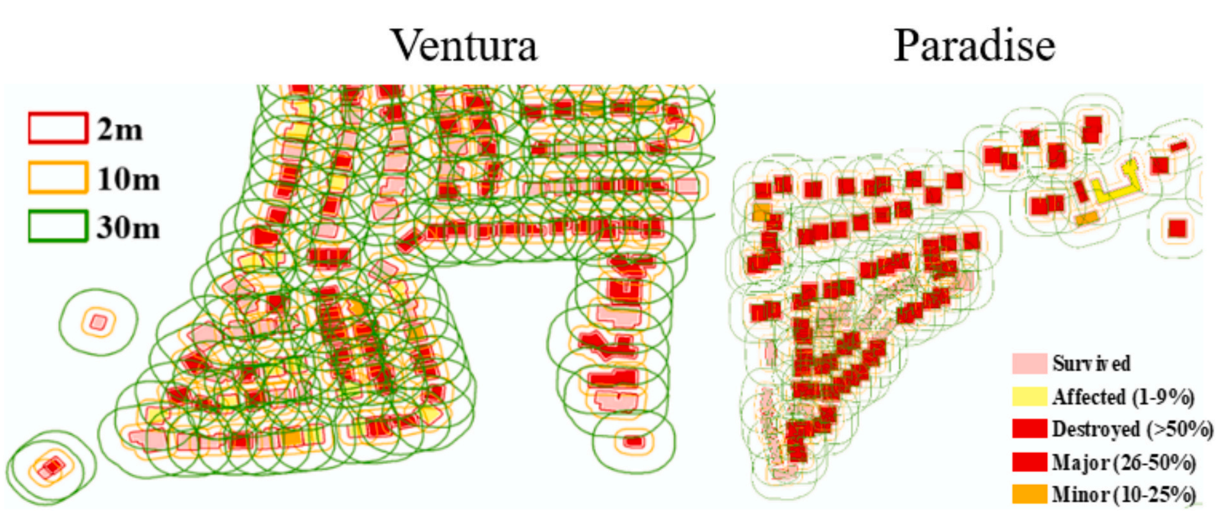

Fig. 2. Examples of the three defensible space buffers (0–2 m, 2–10 m, and 10–30 m) surrounding building footprints and CAL FIRE Damage Inspection Data classes in the Ventura and Paradise, California, USA study areas.

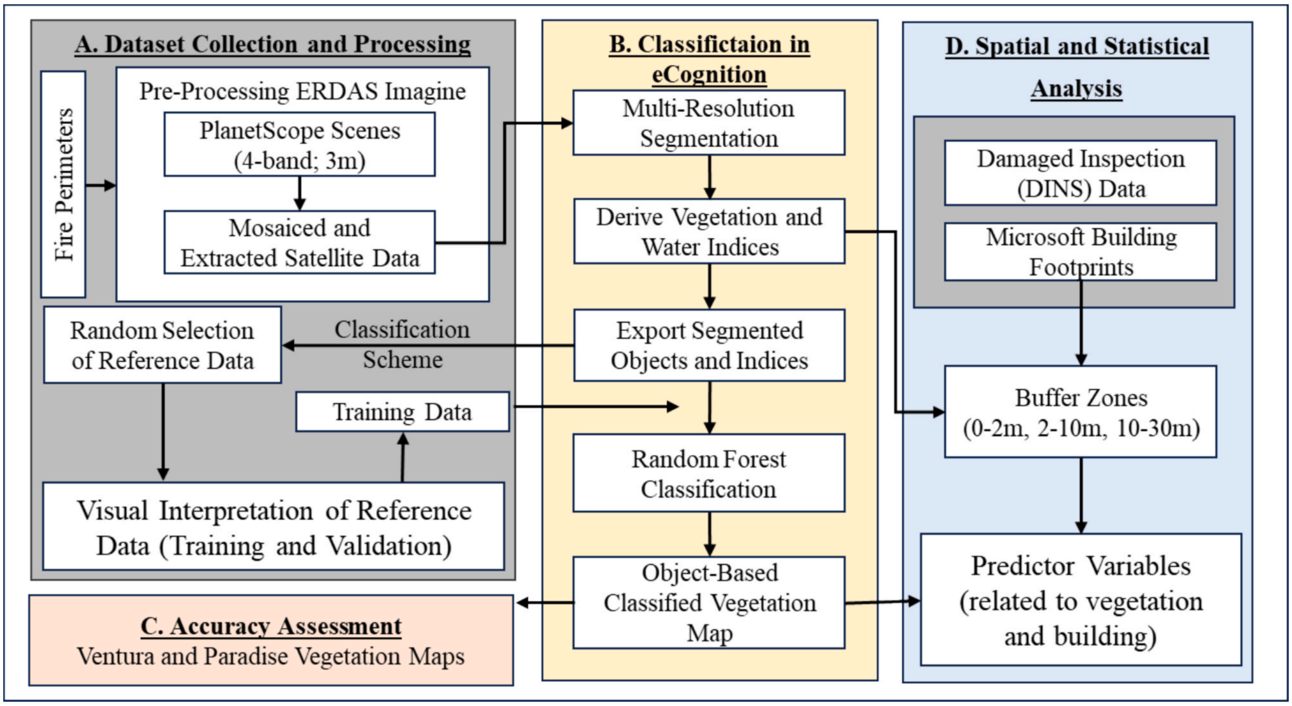

Fig. 3. Four-step (i.e., A-D) work flow used to map parcel-scale urban vegetation types and characteristics in fire-affected neighborhoods in Paradise and Ventura, California, US.

vegetation types included buildings and bare ground (i.e., bare soil, litter cover, wood chips, rocks, gravel, cement, asphalt, wood surfaces and debris).

2.3. Spatial analysis

Vegetation and building variables we analyzed (Table 2) account for: vegetation type, moisture, amount, composition, building characteristics, and density of buildings for the different DSB buffers in the two study areas (Fig. 3-D). Vegetation type characteristics were extracted from the vegetation map for the three DSBs in Ventura and Paradise. First, the polygons for each vegetation type class were extracted and clipped according to buffer boundaries and their characteristics. Second, the area of each vegetation type was estimated in ArcGIS Pro 3.2 using the "calculate area geometry" tool. Then, vegetation greenness and moisture content were derived using Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) based on equations 1 and 2 (Sup. Mat. 1). Specifically, NDVI and NDWI values (-1 to $+\,1$) were extracted for each building's three DSB buffer zones using the zonal statistics tool in Arc GIS Pro 3.2. The NDWI has previously been applied by Maki et al. (2004) to relate vegetation leaf water status to forest fire risk using remotely sensed data.

The NDWI (Table 2) was first developed by McFeeters (2013 and 1996) to delineate and measure surface water bodies. Index values between -1 and 0 correspond to bright surfaces with no vegetation or water content (i.e., droughty), while higher values ($+0$) correspond to higher water content. Subsequently, NDWI was used by Jackson et al. (2004) to map water content in agricultural crops and by Gu et al. (2008) and Jackson (2004) to monitor vegetation drought conditions. Accordingly, NDWI values for water bodies are expected to be greater than 0.5, built-up features will have positive values between 0 and 0.2, while vegetation will have smaller values; thereby facilitating the differentiation of vegetation from water bodies (Table 3; https://eos.com/make-an-analysis/ndwi/). Based on this information, Table 3 lists the 4 NDWI classes used in subsequent vegetation moisture analyses.

The building density variable was estimated by counting the number of buildings (frequency of damaged and survived buildings) in the two most outer DSB (i.e., 2–10 m and 10–30 m) using the frequency tool in Arc Map 10.8.2. The direction and distance of vegetation types, relative to each building, in the 3 buffers were estimated using the 'Near' tool in ArGIS Pro. A near angle measures direction of the line connecting an input feature (i.e., building) to its nearest feature (i.e., vegetation type) at their closest locations. Using the Planar method as distance calculation parameter, the angle is within the range of -180° to 180°, with 0° being east, 90° being north, 180° (or -180°) being west, and -90° is south. The distance units were in meters and angular direction were analyzed as North, South, East, and West directions. The percent of overhanging tree cover occluding each building in Paradise ($n = 1877$) were estimated using the 'Intersect' tool in ArcGIS Pro. Overall, 15–17 variables related to vegetation and building characteristics (Table 2) were divided into the urban-chaparral and urban-forest models that were subsequently analyzed.

2.4. Statistical analysis

The vegetation and building variables (Table 2) were analyzed using Classification and Regression Trees (CART) and are represented in two statistical models: an urban-chaparral and a separate urban-forest model. The simplified urban-chaparral model for Ventura consisted of variables such as building density, and vegetation: types, moisture content, distance, and direction to buildings. While a more advanced urban-forest model for Paradise consisted of these previous vegetation type characteristics and building density plus building construction material, year of construction, and the proportion of tree cover occluding the buildings (Table 2). These two CARTs are also used to represent two disparate urban ecosystems and fuel-fire effects type models (Escobedo et al., 2024).

We then used CARTs and algorithms (Rutkowski e al., 2014) to produce decision trees that determine the predictive relationships between vegetation-building variables and whether homes were destroyed, or survived, during the fire event. A decision tree is therefore also a model or flowchart and associated rules (Kuhn et al., 2014) that lead to two possible *outcomes*; specifically, was the building destroyed or did it survive. Decision trees with fewer splits are less difficult to

Table 2
Variables used to characterize vegetation type, density, moisture, location, building density as well as building distance and direction to vegetation types that were used in both the urban-chaparral and urban-forest models.

Variable type	Variables	Unit	Method/Source
Vegetation	Trees (TreeP)	%	High Resolution Vegetation Map
	Scattered trees (ScatP)	%	
	Shrubs (ShrubP)	%	
	Herbaceous (HerbP)	%	
	Bare Ground (BareGP)	%	
	Vegetation type moisture (Mo_Tree, Mo ScatP, Mo_Herb, Mo_Shrub, Mo_Bare,)	No units	Water Index (NDWI)
	Vegetation greenness (Gr_Tree, Gr_Herb, Gr_Shrub, Gr_Bare)	No units	Vegetation Index (NDVI)
	Direction of Trees in buffer (Dir_Tree)	Azimuth	Near Tool in Arc Map 10.8.2
	Direction of Shrubs in buffer (Dir_Shrub)		
	Direction of bare ground in buffer (Dir_Bare)		
	Direction of Herbaceous in buffer (Dir_Herb)		
	Building Occluding Tree Cover (OverScatP)	%	Intersect and Summary Statistics Tool in Arc Map 10.8.2
	Distance to: Trees/Forest cover patches/Shrub/Bare ground/Herbaceous (Dis_Shrub, Dis_Herb, Dis_Tree, Dis_Bare)	m	Near Tool in ArcGIS Pro
Fire damaged buildings	Distance to Structures (Dis_Str)	m	
	Density of buildings in buffer (Bd_Dens)	No. of buildings per unit area	Frequency tool in Arc Map10.8.2
	Building construction (before 1997, 1997–2008, after 2008) (Built_Yr)	Year	Damage Inspection Schema data from CalFire
	Building/roof construction material (Roof)	Asphalt, metal, tile, concrete	

Table 3
Normalized difference water index (NDWI) classes and values from −1 to + 1.

NDWI	Description
0.2 – 1	Water surface
0.0 – 0.2	Flooded, humid areas, high vegetation moisture content
−0.3 – 0.0	Moderate drought, non-water surfaces
−1 – −0.3	Droughty, low vegetation moisture content, non-water surfaces

interpret than decision trees with many splits. This makes small decision trees (e.g., 2 or 3 splits) ideal for generating simple heuristics that can inform policy (Rutkowski et al., 2014), However, when interpreting splits to inform policy, care is needed when selecting variables for the decision tree model so that erroneous splits are less likely (Kuhn et al., 2014).

The CARTs (Breiman and Freedman, 1983) were implemented using a classification approach since the response variable *Outcome* is categorical. The primary objective of this approach was to identify the most influential vegetation and building factors associated with building destruction during the two fire events. The selection of hyperparameters, specifically the complexity parameter (CP), was conducted using 10-fold cross-validation to balance model complexity and applicability. This approach prevented overfitting while ensuring that decision trees can be interpreted. To do so, we adjusted the CP by iteratively pruning the decision tree at different thresholds and selecting the optimal value that minimized cross-validation error. Multiple rounds of cross-validation were performed to enhance the robustness of hyperparameter selection. The final CP value was chosen based on the average performance across iterations to ensure consistency in model selection.

We used the Adaptive Least Absolute Shrinkage and Selection Operator (Adaptive LASSO; Zou, 2006) for feature selection. This allowed us to retain the most relevant predictor variables while reducing redundancy and potential collinearity; thus refining the model and improving its predictive power while facilitating its interpretation. The response variable (i.e., *Outcome*) is a binary categorical variable and indicated whether a building was destroyed (1) or survived (0) during the fire event. The predictor variables used in the CART model were selected based on ecological, spatial, and structural factors listed in Table 2. These variables account for factors that have bene reported to influence wildfire impacts including: vegetation cover, moisture, spatial configuration, directional influence, and building characteristics (Alexandre et al., 2016a, 2016b; Syphard and Keeley, 2019; Van Der Kamp, 2017).

The final CARTs were applied to the two study areas to create the urban-chaparral model and a separate urban-forest model. For the urban-chaparral model in Ventura, we incorporated vegetation variables such as type, moisture, distance, and direction. The urban-forest model or Paradise combined building characteristics (e.g., roof material, year built, building density) with overstory vegetation structure. This integration allowed us to assess the combined influence of both natural and built environmental features on building survival. All statistical analyses were conducted using R version 4.1.2. The CARTs were developed using *rpart* version 4.1.16 package (Therneau et al., 2015) in R and the final decision tree model was visualized with the *rpart.plot* function (https://CRAN.R-project.org/package = rpart.plot), highlighting the most influential variables for determining building destruction risk. This graphical representation provides an intuitive understanding of how environmental and structural factors interact to influence wildfire outcomes. For specific methods on the LASSO model approaches as well as development and interpretation of the decision trees, please refer to the **Supplementary Methods** section.

3. Results

3.1. Vegetation type map and building loss

Urban vegetation type maps consisted of shrub, herbaceous, tree, bare ground, herbaceous as well as buildings (Fig. 4) and a scattered tree (ScatP) type and a percent building occluding tree cover (OverScatP; Table 2) for Paradise. We also developed vegetation moisture maps for the three DSB buffers surrounding each building in Ventura and Paradise using Equation 2 as shown in Fig. 5. The overall accuracy of vegetation maps for Ventura and Paradise were 90 % and 88 %, and Kappa indices were 0.73 and 0.72 respectively; metrics that are considered relatively high accuracies (Congalton and Green, 2019). In terms of individual classes, herbaceous and shrubs had slightly higher errors of commission (low user accuracy) than trees and bare ground (**Supplementary Results 2**). The accuracy of buildings class was not assessed because Microsoft building footprint and DINS damage inventory data were used to label all the building objects. However, in Ventura and Paradise, there were 1230 and 16,319 buildings, respectively, within the fire perimeters. Of these, 35 % and 88 % were destroyed in Ventura and Paradise, respectively.

3.2. Vegetation type and building characteristics, defensible space buffers, and building loss

The urban-chaparral model (Table 4, Fig. 6a) shows that in DSB 1, a bare ground cover (BareGP) of less than 19.86 % is the most important predictor of building loss. Specifically, 6 % of buildings immediately

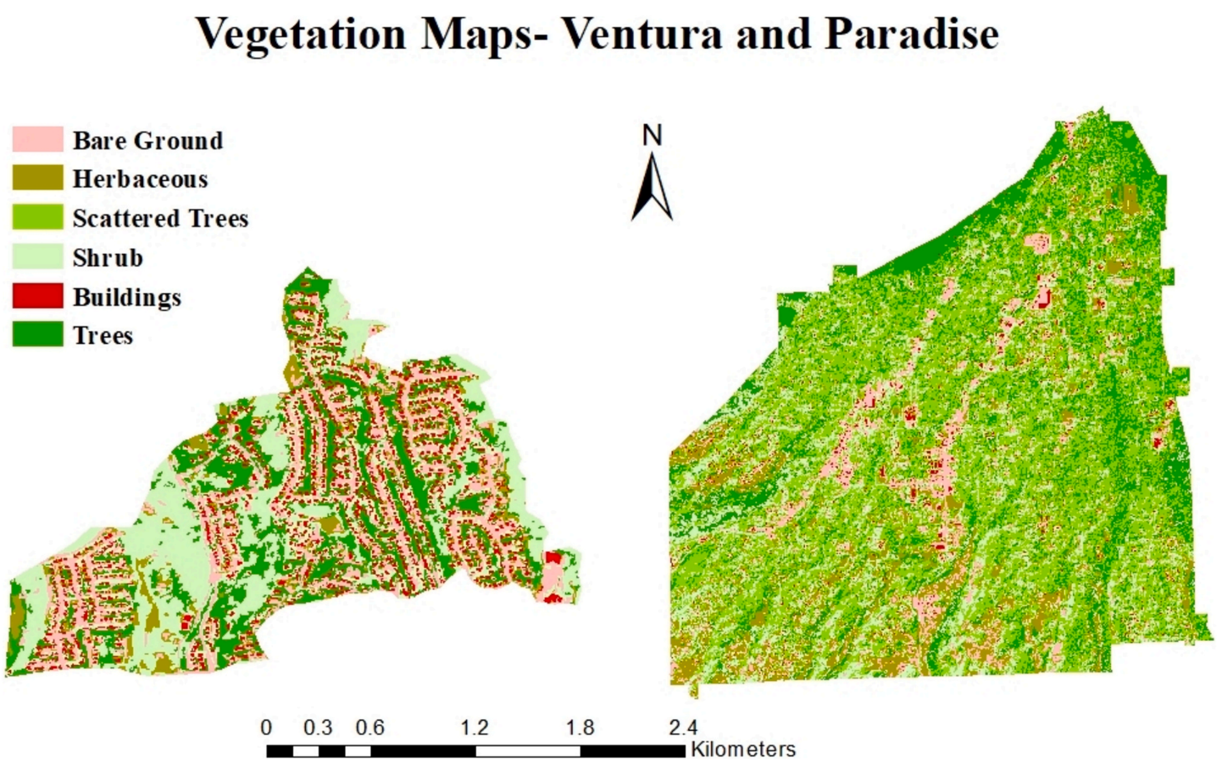

Fig. 4. Urban vegetation type map for Ventura (left) and Paradise (right) developed using Planetscope satellite data and object-based classification in eCognition software at 3 m spatial resolution for pre-fire 2017 and 2018.

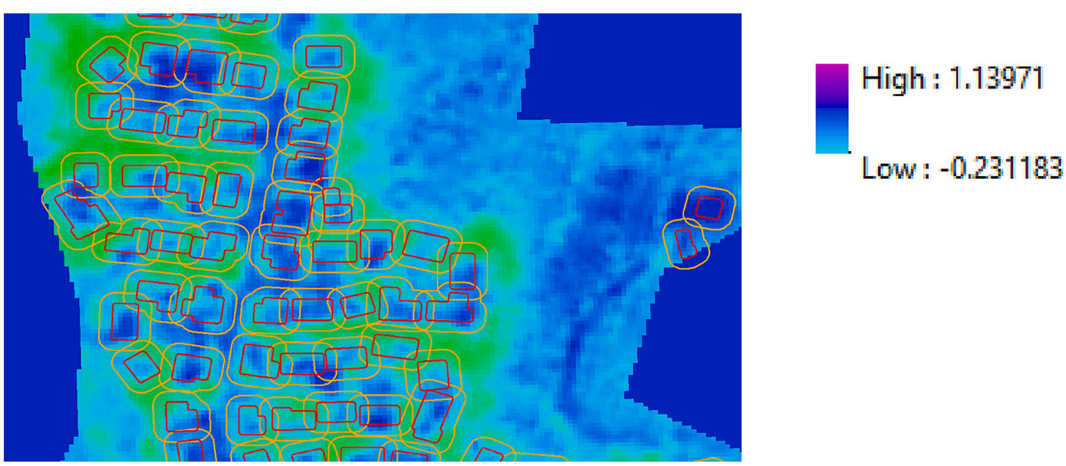

Fig. 5. Example of the Normalized Difference Water Index (NDWI) map used for the three different Defensible Space Buffers surrounding buildings in a fire affected neighborhood in Ventura, CA.

adjacent to bare ground cover less than 19.86 % and trees with moisture indices less than −0.43 moisture (i.e. droughty), were more likely to be destroyed. Conversely, 94 % of buildings in all other scenarios (e.g., bare ground covers greater than 19.86 %, NDWI tree moistures more than -0.43) for DSB1 were more likely to survive. Specifically, homes with more than 20 % bare ground cover and with trees with higher moisture content near them, were more likely to survive (Fig. 6a).

In DSB2, when herbaceous moisture indices were greater than −0.084 (i.e., less droughty; Fig. 6b; Table 4) and some criteria are met regarding distance to trees and direction of shrubs, the path predicted building survival for 37 % of buildings. Similarly, when herbaceous moisture was greater than −0.084, distance to trees was less than 8 m, the directional degrees of shrubs was less than 116, and the distance to bare ground was greater than 5.2 m, 6 % of buildings were more likely to be destroyed. When herbaceous moisture indices were less than −0.084 (i.e., more droughty) the decision tree presented more nuanced findings concerning building loss relationships in DSB2 because more terminal nodes predicted destroyed buildings than on the less droughty side. However, the first node predicting destroyed buildings only requires one additional split, that shrub moisture be less than −0.41 (Fig. 6b). This produces the parsimonious rule for DSB2 that buildings with herbaceous moisture less than −0.084 and shrub moisture less than −0.41 (i.e., droughty herbaceous and shrub vegetation types) in this buffer predict 4 % of buildings lost.

Finally, for DSB3 the most important split for predicting building loss was whether percent bare ground was greater or less than 41 % (Fig. 6c; Table 4). When bare ground is less than 41 % and distance to herbaceous vegetation (Dis_Herb) is greater than or equal to 25.97 m to the building,

Table 4
Estimated decision tree results for the Urban chaparral model, listed in order of inferred importance for building destruction or survival according to Ventura Defensible Space Buffer (DSB) 1 (0–2 m), 2 (2–10 m), and 3 (10–30 m).

Significant Variables	**Buffer 1 estimates, predictors and paths;** (Inferred importance ranking); [Model estimate per DSB]
% Bare Ground	< 19.86 % (2)
Tree Moisture	< −0.43 (4)
	Buffer 2 estimates
Herbaceous moisture	>= −0.084 (2)
Tree Distance*	< 10 m [8 m] (3)
Direction to Shrub	<116 (4)
Shrub moisture	< −0.41 (6)
Distance to bare ground*	>= 7.17 m [5.17 m] (16)
	Buffer 3 estimates
% Bare Ground	< 41 (2)
Distance to herbaceous*	>= 25.97 m [15.97 m] (4)
Building density	>= 8.5 (6)
Tree Distance*	>= 14.41 m [4.40 m] (10)
Tree Direction	Southwest [< −155.21] (14)
Distance to Structures*	< 15.35 m [5.34 m] (44)

*Actual distance to buildings.

the model predicted that 11 % of buildings were destroyed. Also, the model predicted 1 % of buildings were destroyed when bare ground is less than 41 %, distance to herbaceous is less than 15.97, and distance to trees was greater than or equal to 4.4 m. Conversely, 62 % of buildings were predicted to survive (Fig. 6c), where for these buildings bare ground is greater than 41 %, building density is less than 9, and the direction of trees is greater than 155 degrees (west-southwest).

In the urban-forest model, bare ground cover was a key variable in predicting building loss in DSB1 (Fig. 7a; Table 5). Overall, the most parsimonious path for predicting building loss, was when bare ground covers were less than 9.27 %, or when bare ground covers were greater than 9.27 % and distance to bare ground is less than 0.02 m (94 % of buildings). The most parsimonious path for predicted building survival (6 % of building) was when bare ground cover was greater than 9.27 % and distance to bare ground was greater than 0.02 m. Similarly, if Bare ground was greater than 9.27 %, Distance to bare ground was less than 0.02 m, Distance to herbaceous cover was greater than 1.1 and Overstory tree cover was less than 10 %, predicted that 2 % of buildings surviving.

In DSB 2, droughty shrub moisture content (Mo_Shrub, −0.5) was the most important predictor for building class, but nearly every model path led to building loss and paths that led to building survival contained fewer than 1 % of homes; therefore the model might not be as helpful in this specific DSB for predicting building loss or survival (Table 5; Fig. 7b). However, the path containing the greatest number of destroyed buildings, more than all other paths combined, is when together shrub moisture was greater than −0.5 and building density was less than 2. Similarly, droughty shrubs (Mo_Shrub < -0.5 and < -0.6) and droughty scattered trees (Mo_Scat_tree −0.06) also predicted 52 % buildings destroyed.

In DSB 3, we see that nearly every path leads to a prediction of building loss (Fig. 7c); particularly when distance to scattered trees was less than 10.01 m (86 % of buildings). For the remaining 14 % of buildings where distance of the scattered trees is greater than or equal to 10.01 m, there is only one path that leads to predicted survival. Specifically, when distance to scattered trees is greater than 10.01 m, building densities were less than or equal to 6, bare ground moisture was

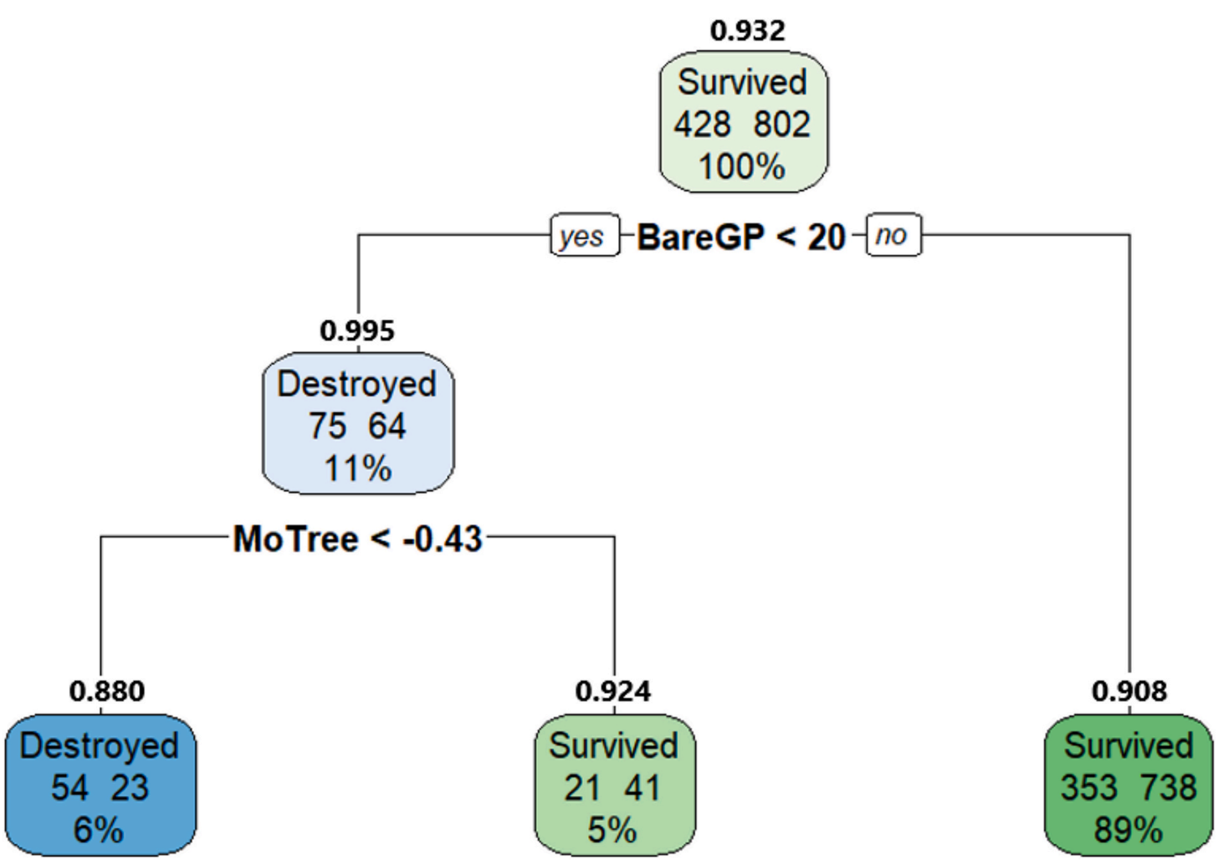

Fig. 6. Estimated decision trees for the urban chaparral model for Ventura, California's Defensible Space Buffers (DSB) 1 (Fig. 6a), 2 (Fig. 6b), and 3 (Fig. 6c). The values inside the nodes represent the predicted class (i.e., survived or destroyed), the predicted number of buildings in each class (destroyed and survived), and the percentage of buildings that were either destroyed or survived within the node. Entropy is indicated above each node.

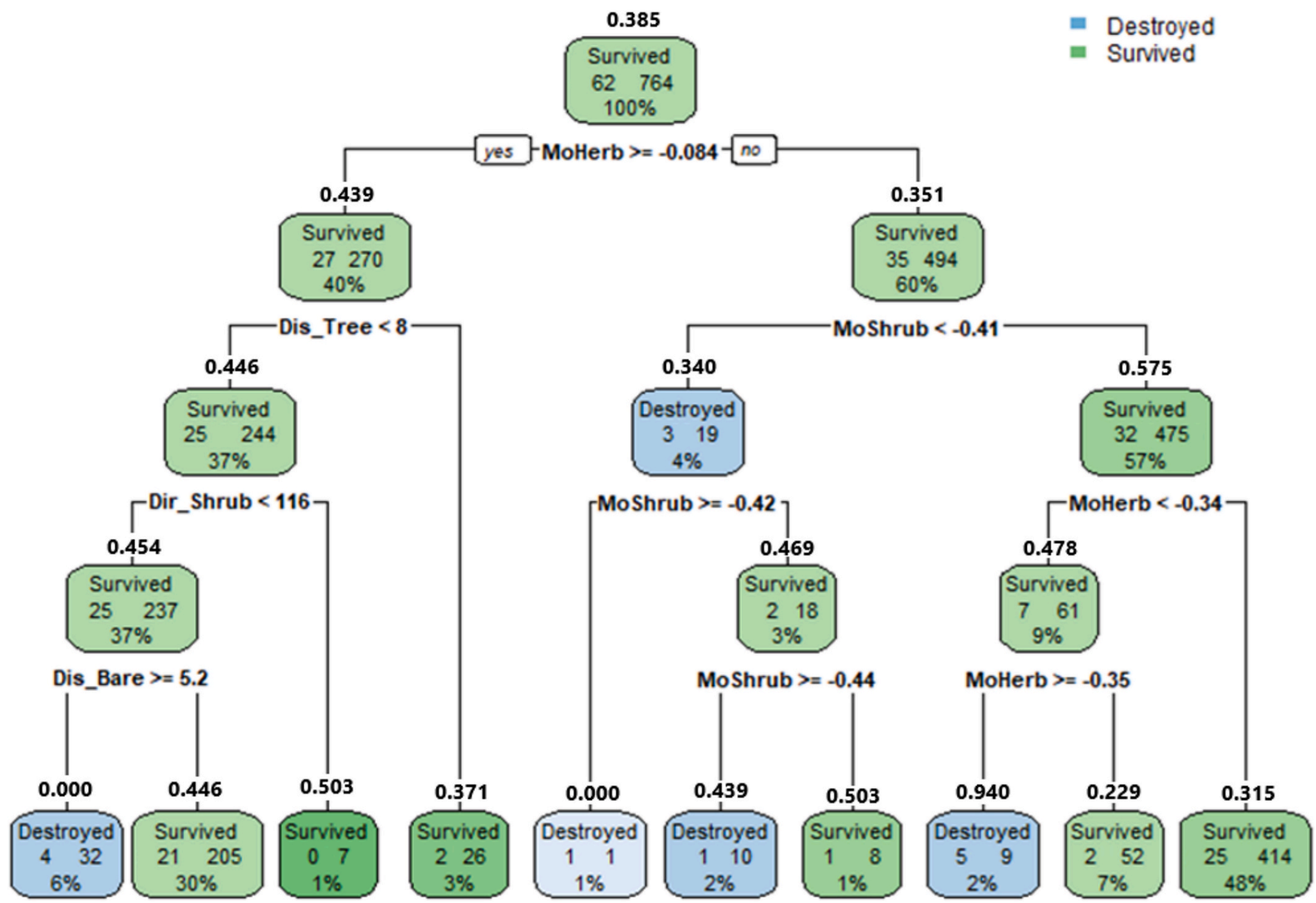

Fig. 6. (*continued*).

less than or equal to −0.28 (less droughty), and distances to herbaceous vegetation was greater than 10.05 m. Unlike DSB 2, the path that leads to building survival contains only 3 % of the buildings, so the model is more helpful at predicting building survival.

4. Discussion

Our methods and findings provide for a more nuanced understanding of the complex interactions between different vegetation types and building loss, or survival, during urban fire events in two fire-prone urban ecosystems in California US. Although studies such as those of Knapp et al. (2021), Syphard et al. (2014), Gibbons et al. (2012) and Troy et al. (2022) have documented the role, and importance, of building characteristics in building loss; our study presents novel findings regarding the role of different urban vegetation or fuel types in building loss across DSBs. In doing so, our study provides for a better understanding of the trade-offs associated with urban vegetation-related ecosystem services (e.g., temperature regulation, increased property values) and increased fire risk (i.e., ecosystem disservice; Cheng et al., 2024) in fire-prone urban ecosystems in places such as North and South America, Australia, and southern Europe, (Cruz et al., 2012; Escobedo et al., 2024).

The urban vegetation type maps for Ventura and Paradise display in a spatially explicit manner the heterogenous distribution of urban vegetation and fuels relative to residential buildings (Fig. 4). Previous studies have focused on mostly “structural” characteristics and a few tree cover variables often estimated using 30 m resolution satellite and aerial imagery (Knapp et al., 2021; Kramer et al., 2019; Syphard et al., 2014). Conversely, our study accounted for tree, shrub, and herbaceous types, moisture, and cover characteristics, as well as building occluding tree cover, scattered tree patches, tree and shrub distance and direction, as well non-vegetation factors such as bare ground and building characteristics (Table 2).

Studies such as those of Neyns and Canters (2022) have documented the advantage of using recent high resolution satellite data for mapping and monitoring the phenological and taxonomic characteristics of urban vegetation. Especially, with the use of supervised, non-parametric classification method and the launch of satellites with short revisit times and improved spectral and spatial resolutions (e.g., PlanetScope, RapidEye). Also, other urban vegetation mapping studies using random forest classification methods and object-based classification of high resolution maps have reported accuracies similar to our study of 80–84 % (Gibbes et al, 2010; Sicard et al., 2023). As such, our 3.0 m resolution maps produced using object-based classification, eCognition and our accuracy assessment metrics can provide for more accurate, yet less time-consuming classification approaches for mapping parcel-scale vegetation types, than other pixel-based algorithms (Bhaskaran et al., 2010, Knapp et al., 2021). Therefore, studies such as ours can provide for a better understanding of parcel-scale vegetation composition, structure and fire dynamics around urban and WUI homes (Figs. 4 and 5; Chen and McAneney, 2004).

Similarly by using NDWI, we also explore the role that vegetation moisture, and indirectly drought and irrigation practices, can play in determining building loss during fire events (Gibbons et al., 2018; Fig. 5). This is exemplified in our urban-chaparral model, where homes with low bare ground cover (~20 %) and with trees with high NDWI moisture content (−0.43) near them, were more likely to survive (Fig. 6a). This has implications for tree removals (i.e., fuel hazards) near

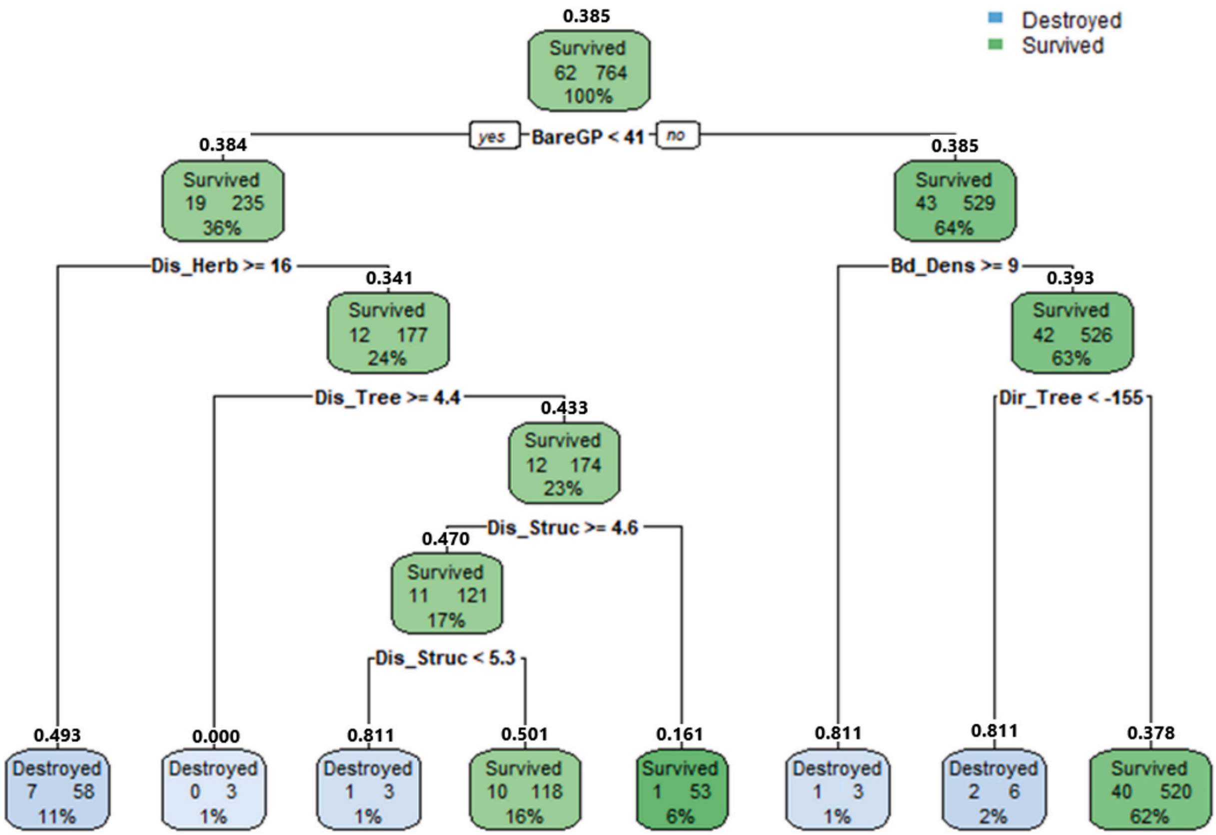

Fig. 6. (*continued*).

homes (Fig. 6a-6c) and for urban fire risk mitigation practices like "fire-smart" plant selection and design, proper irrigation, and pruning practices in fire-prone urban landscapes (Gibbons et al., 2012; Troy et al., 2022). Our vegetation type, moisture, density and cover analyses complement the other building-related factors that have been reported to predict home loss or survival in shrubland and forest-dominated urban ecosystem (See Section 1). For example, Syphard et al (2014) reported that in chaparral dominated San Diego County US, the most effective DSB for building survival was 5–20 m while distances > 30 m had little additional benefits. Although these authors report that percent vegetation cover in the first 2 DSB was most effective, we also found that low tree, shrub and herbaceous NDWI moisture levels were also significant predictors of building loss in the urban chaparral model (Table 4). Conversely, high NDWI moisture trees near homes were significant predictors of building survival in this same model (Fig. 6a). That said, Mockrin et al. (2023) reported that building materials and landscape-level characteristics in shrubland-dominated areas of Los Angeles County, USA were more influential in determining building outcomes than vegetation characteristics. Again, emphasizing that building characteristics are more important than vegetation types and characteristics in DSBs 1–3 in influencing building loss during fire events (Fig. 6).

In Paradise, our urban-forest model also estimates that amount and proximity of bare ground immediately next to the home as well as distance to herbaceous cover types were the most significant predictors of building loss, while percent occluding overstory tree over the home, was a much less influential predictor in DSB 1 (Table 5). The consistent significance of bare ground cover in predicting building loss across many DSBs in both our models was noteworthy and has not really been documented before (Figs. 6 and 7). However, it is important to note that our bare ground cover type also consisted of flammable fuels such as litter, mulch, vegetation debris or even flammable wooden decks or fences, which can increase the risk of fires or fire spread (Knapp et al., 2021). Similarly, bare soil or even concrete and pavement were also classified as bare ground. The less influential role of occluding or overstory tree cover is also informative (Table 5). Litter generation and possible flame contact from such trees has been reported as a factor in building loss and thus overstory tree cover is regulated in WUI-fire risk ordinances (Syphard et al., 2021; Troy et al., 2022). However, these tree crowns might be shielding homes from embers (Keeley and Syphard, 2019). Post-fire observations by the authors have also noted many instances where burning homes were the heat or flame source for nearby tree scorch and consumption.

Studies from Paradise CA have explored the influence of building characteristics, and broadly defined vegetation cover classes on building outcomes during the Camp Fire. Knapp et al., (2021) found that the "relative importance of nearby burning structures versus surrounding vegetation in explaining home survival" was variable. They found that greater distances between buildings, as well as overstory tree covers of less than 53 % in distances greater than 30 m, had a larger effect on home survival; than did tree cover within our DSBs (0–30 m). Troy et al.'s (2022) analysis found "less conclusive" and mixed results when analyzing the role of DSB vegetation cover and practices in building loss. They did however find that increased amount of dead grass near structures, and litter on roofs/gutters, were associated with increased building loss.

Other studies elsewhere in California have also explored the role of broadly defined vegetation and tree cover and amount, as well as defensible space, on building loss during fire events (Knapp et al., 2021; Syphard et al., 2014). For example, Syphard and Keeley (2019) study based on more than 40,000 structures in urban and WUI fire events concludes that building characteristics were more influential in reducing building loss than vegetation characteristics within the DSBs. Syphard et al, (2021) found no direct relationship between vegetation and building loss during fire events in the San Francisco area, interior north and southern California regions. Although vegetation less than 25–30 m from buildings was more influential in building loss than more distant

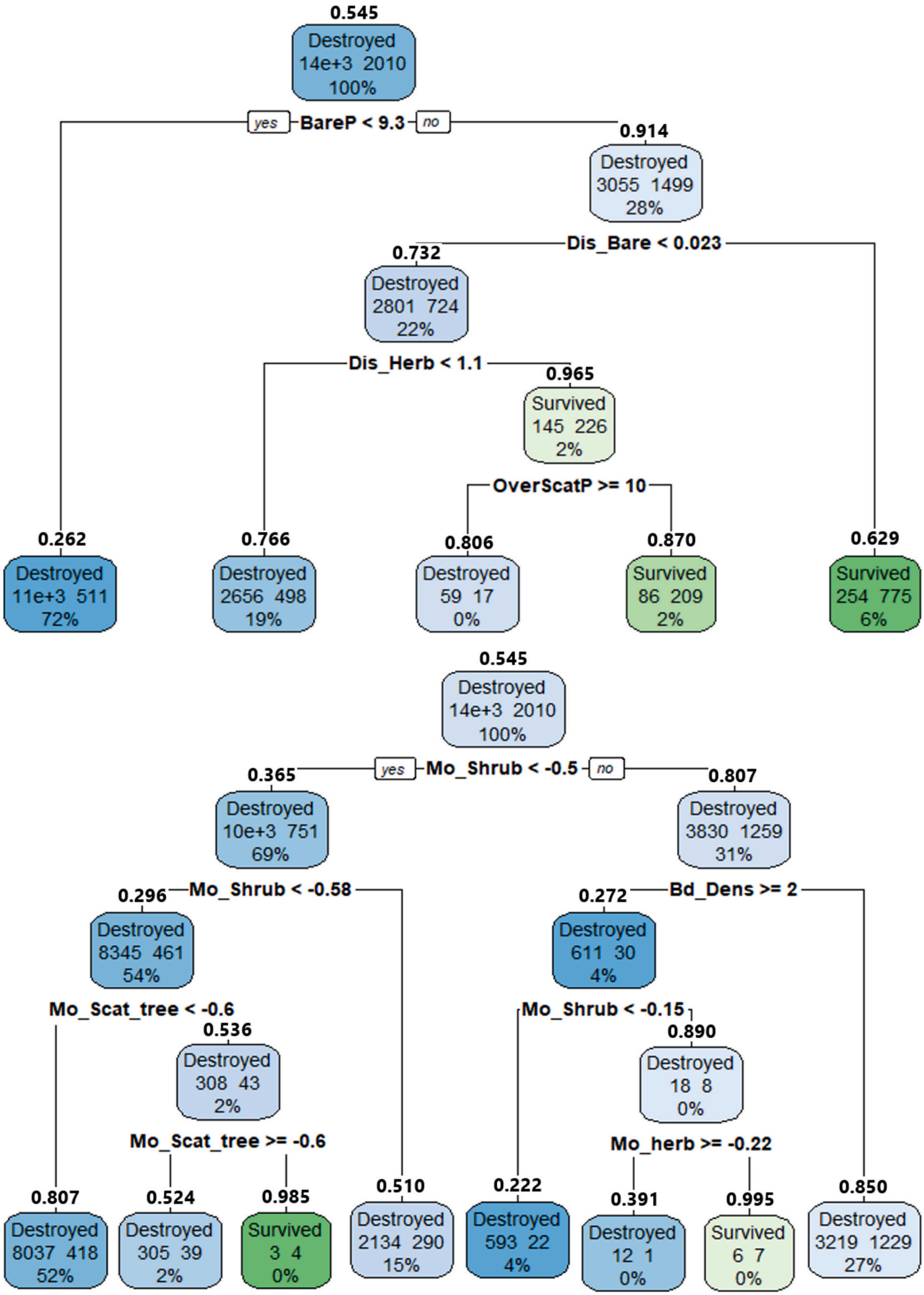

Fig. 7. Estimated decision tree results for the urban forest model for Paradise, California's Defensible Space Buffers (DSB) 1, 2 and 3. The values inside the nodes represent the predicted class (i.e., survived or destroyed), the predicted number of buildings in each class (destroyed and survived), and the percentage of buildings that were either destroyed or survived within the node. Entropy is indicated above each node.

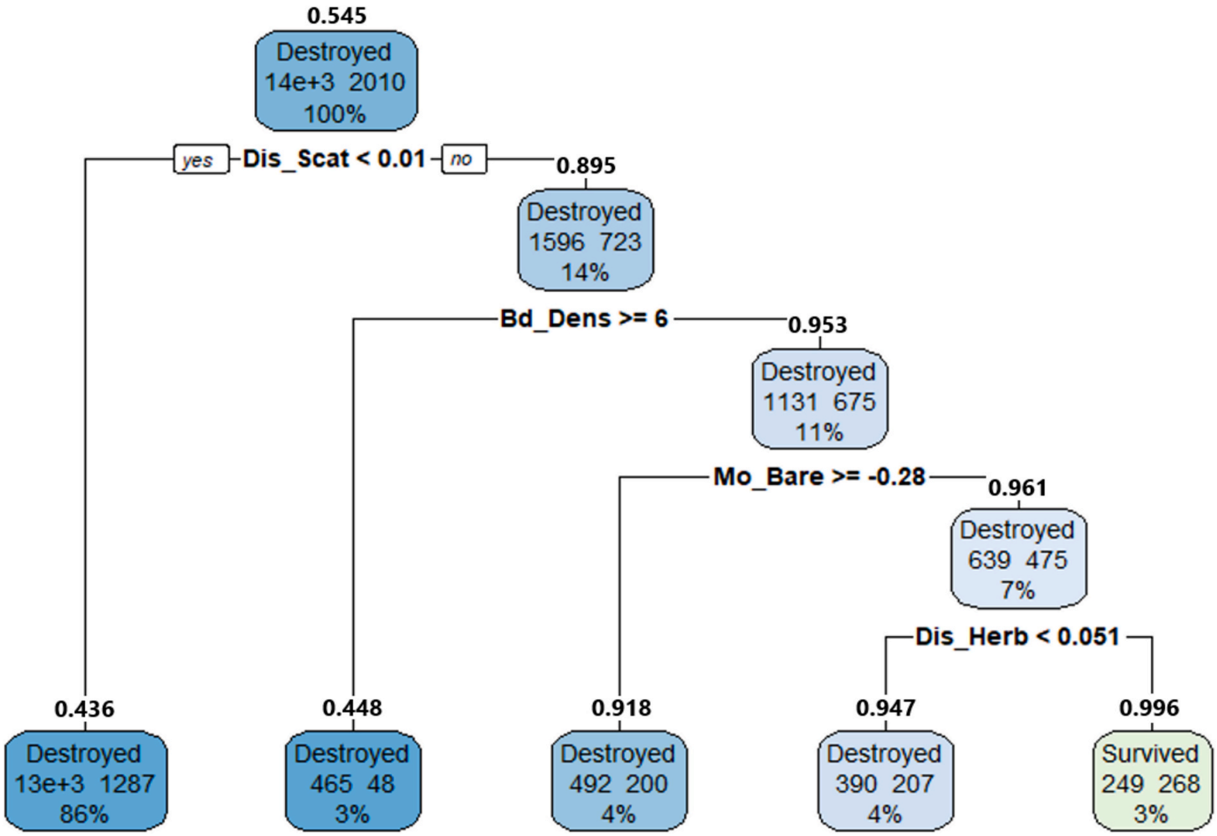

Fig. 7. (*continued*).

Table 5
Estimated decision tree results for the urban forest model for Paradise California's Defensible Space Buffers (DSB) 1 (0–2 m), 2 (2–10 m) and 3 (10–30 m).

Significant Variables	DSB 1 estimates; (Inferred importance ranking); [Model estimate per DSB]
% Bare Ground	< 9.27 % (2)
Distance to bare ground*	< 0.02 m [0.02 m] (6)
Distance to herbaceous*	<1.1 [1.13 m] (12)
% Overstory cover	>= 9.98 % (26)
	DSB 2 estimates
Shrub moisture	< −0.50 (2)
Building density	>= 1.5 (6)
Scattered tree moisture	< −0.59 (8)
	DSB 3 estimates
Distance to scattered trees*	< 10.01 m [0.01 m] (2)
Building density	>= 5.5 (6)
Bare ground moisture	>= −0.27 (14)
Distance to herbaceous*	< 10.05 m [0.05 m] (30)

*Actual distance to buildings.

vegetation, overall housing density and characterises (i.e. patterns) were more influential than local-scale vegetation in determining building loss outcomes (Schmidt 2022; Syphard et al., 2021). However, our parcel-level study complements other studies from California such as Kramer et al, (2019) and Syphard et al. (2021), by focusing on factors that have previously been little studied, specifically vegetation composition, type, moisture and location relative to burned buildings (Tables 2).

Overall, we found that tree, shrub and herbaceous moisture were better predictors of building loss than was overstory tree cover in DSBs 1–2 for both models (Tables 4 and 5). Studies from other WUI fires in Mediterranean climates such as Gibbons et al. (2012) found that home loss in southeastern Australia was associated with increased tree-shrub cover and composition (i.e., remnant or planted) within 40 m of the structure. Another study from Australia using vegetation cover classes within 20 m of a structure, found that vegetation cover "touching" or "overhanging" homes was related to increase loss, therefore risk was reduced by reducing vegetation cover, amount, and proximity to homes (Penman et al., 2019). Similarly, in central Chile, Aguirre et al., (2024) using high-resolution optical ortho mosaics from drones, found that homes located close to broadly defined NDVI vegetation classes, had "slightly higher" odds of damages at distances < 60 m from homes. However, contrary to these studies from Australia and Chile using broad tree cover class-based metrics (Knapp et al., 2021; Syphard et al., 2017a, 2014; Troy et al., 2022), our study is one of the first to specifically analyze the influence of parcel-level 3.0 m resolution: vegetation type, densities, and moisture as well as its distance and direction relative to DSB and building loss (Figs. 5, 6 and 7).

Although the role of building characteristics in their survival during WUI fire events has been well documented as outlined in our literature review, the role of parcel-scale urban vegetation characteristics has not. Alexandre et al. (2016a) for example did find that clusters of buildings were associated with a greater probability of loss, particularly in more densely populated WUI areas. Syphard et al. (2012) also used these broad vegetation cover classes (U.S. Geological Survey National Land Database; mrlc.gov) and found that housing arrangement and location were the most important contributors to property loss in the WUI fires. In terms of building characteristics and their role in survival, Knapp et al. (2021) found that homes constructed after 1997 demonstrated a 38 percent survival rate, whereas pre-1997 constructions exhibited only an 11.5 percent survival rate. Similarly, Baylis and Boomhower (2021) found that homes built in 2010 or later, three years following the implementation of updated building codes, were 15 percentage points less likely to be destroyed compared to those constructed in 1985 under similar wildfire conditions.

Our study contributes to the fire-building loss literature by analysing the role of different urban vegetation types and their condition (i.e., moisture, location, and density; Table 2; Fig. 5) to home loss/survival in residential neighborhoods during urban fire events. Findings indicate that properly selected, irrigated, located, and maintained urban vegetation is not always complicit in building loss during fire events. Furthermore, we corroborate how dense urban or suburban developments (i.e. 2–9 structures within 30 m; Tables 4 and 5) are more susceptible to widespread building damage during wildfire events; regardless of parcel-level or landscape-level vegetation fuel characteristics. And as expected, burning buildings likely acted as sources of not only embers, but direct flame contact and radiant heat that can ignite nearby structures as shown by Suzuki et al. (2014).

Previous studies have called for stricter construction codes and building practices (e.g., non-combustible siding material, dual pane windows, fire-resistant roofing and construction materials; Knapp et al., 2021); these can however be very expensive. Also, other studies and policies recommend that urban development in high-fire risk areas be highly regulated by limiting new residential construction or integrating strategic open spaces to disrupt fuel continuity (Moritz et al., 2014; Syphard et al., 2017a). However, these land use options are likely difficult to implement in high real estate premium contexts. Accordingly, our study provides some basic low-cost options related to vegetation management in urban areas.

Like these other studies, our findings suggest that along with urban land use patterns, urban vegetation moisture and type, can play a role in influencing a building's vulnerability to fire (Fig. 5). For example, the moisture and amount of low growing vegetation types (i.e., shrubs and herbaceous) and bare ground covers (e.g., mulch, litter) in DSB1 are highly influential in building loss (Tables 4 and 5). Conversely taller vegetation (i.e. trees) in DBS 1 and 2 that is droughty and closer to buildings, did influence - but to a lesser degree - building loss in both Ventura and Paradise (Tables 4 and 5). Therefore these findings provide evidence for "*defensible* space" guidelines and municipal ordinances that emphasize that although these zones can alter fire behaviour around homes, their main purpose is to improve fire fighters access to better *defend* homes during fires (https://readyforwildfire.org/prepare-for-wildfire/defensible-space/). Our findings also suggest that WUI-based vegetation management practices and guidelines that are recommended for DSB3 in urban ordinances and planning instruments are less relevant and very difficult to implment. First because building density and distance to other buildings were more influential than vegetation characteristics. And second, urban parcels are usually smaller in area than WUI parcels, thus DSB3 is often not present or can overlap onto a neighbouring parcel's DSB2 (Escobedo et al., 2024).

We do note some limitations in our study. First, we note that CART algorithms are sensitive to collinearity between input variables, and this can lead to erroneous splits in the estimated decision tree. This has implications when interpreting our vegetation moisture findings as this variable is closely correlated with vegetation greenness and amounts. Second, we did not focus on building characteristics but rather on parcel-level vegetation composition, types, amounts and moisture. As shown in our urban-chaparral model, we were not able to account for these building variables due to lack of data availability (e.g., building materials) and both spatial and non-spatial inconsistencies in available datasets (e.g., year built). However, we did account for construction year and roof surface material type in our urban-forest model. Third, we admit that our bare ground cover non-vegetation type, is still too broad to sparse out how non-vegetation ground cover types (i.e., bare soil, concrete or wood surfaces) influence building loss during fires. And finally, we did not account for the role of tall, moist, vegetation "filtering" wind-borne embers or – conversely – producing flammable litter, nor individual home owner or fire fighter actions in defending homes and influencing home survivability.

5. Conclusion

Our findings and approach could be used to further study and better understand the tradeoffs society makes between urban ecosystem services versus disservices in warm, drought and fire prone urban biomes. Specifically the use of well-maintained urban vegetation types near homes for climate regulation, aesthetics, and human well-being versus the increased risk of wildfire and home ignition due to increased fuels adjacent to homes. For example, our study corroborated the importance of building construction codes, practices, and building density on damage to structures during fire events. But the significance of bare ground cover (i.e., litter, mulch, wood surfaces) as well as building densities in predicting building loss across many DSBs further adds to this understanding. We also document how tree, shrub, and herbaceous moisture in yards are better predictors of building loss – or survival – than just percent vegetation cover alone. Indeed according to our urban chaparral model, homes with nearby trees with higher NDWI moisture content were more likely to survive. This influential role of high moisture tree cover – relative to other factors- in home survival has rarely been documented. Such information can have implications for designing insurance regulations and vegetation ordinances, as well as urban plant selection, design, irrigation, and landscaping practices.

Our parcel-level study, while not focusing on buildings or the WUI, does however provide novel insights into home-property level processes around buildings, in terms of urban ecosystem structure, composition and vegetation density. By also examining different DSBs of interest around fire-affected buildings, our analysis also provides improved insights into the effectiveness of traditionally used fire risk mitigation practices. As fire increasingly affects urban ecosystems, this information sheds light on how relevant DSBs and WUI guidelines and fuel management practices are when applied to more densely urbanized, highly populated neighborhoods with diverse, heterogenous vegetation composition. The findings also provide insights into how homes in different ecosystems and fuel regimes interact with certain urban vegetation types and established defensible space guidelines. Our use of advanced object-based classification techniques to map urban vegetation composition, structure and distribution – as opposed to commonly used pixel-based land cover type-based approaches also provides an alternative approach for more rapid mapping of urban ecosystem characteristics and fuel types.

In conclusion, recently many home insurance providers and landscaping ordinances in California are requiring homeowners to remove all vegetation, particularly trees, near homes in high wildfire hazard areas or risk fines or cancellation of insurance policies. But most of the literature we reviewed, and our findings suggest that in urban fire events it is primarily building characteristics (i.e., building density), dry flammable structures (e.g., wood fences and decks) near homes, firefighting operations, and fire weather – and to a much lesser degree parcel-level urban vegetation composition and structure – that are most influential in building loss or survival. Thus, proper pruning, irrigation, and placement of ground covers and vegetation are key in determining the right balance between the ecosystem services benefits of urban vegetation, versus the ecosystem disservice costs of increased fire risk and hazard. Our study underscores the importance of urban planning as well as both landscape practices and building regulations in enhancing building resilience against wildfires. It also highlights the limits of applying guidelines that were developed in more rural, low housing density WUI contexts, to highly urbanized land use cover types that are now increasingly being affected by urban fires globally.

CRediT authorship contribution statement

Francisco J. Escobedo: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kamini Yadav:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Onofrio Cappelluti:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis. **Nels Johnson:** Writing – original draft, Supervision, Methodology, Investigation, Formal analysis.

Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2025.105421.

Data availability

Data will be made available on request.

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