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Modeling Neighborhoods as Fuel for Wildfire: A Review

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Abstract
Wildfire's destruction of homes is an increasingly serious global problem. Research indicates that characterizing home hardening and defensible space at the individual structure level may reduce loss through enriched understanding of structure susceptibility in the built environment. However, improved data and methods are required to accurately characterize these features at scale. This paper does three things: (1) Identifies features correlated with structure loss. (2) Compares methods of characterizing structure susceptibility, including home assessments and emerging fire spread models. (3) Evaluates methods and open data sources used to measure these features. We find that relative feature importance varies widely among studies due to data limitations and scale issues. Built-environment fire spread models show limited inclusion of structure-level features. Additional research, model validation, improved data, and improved data collection methods are needed to bridge the gaps between primary research, susceptibility indices, and built-environment fire spread models. Advancing scalable methods for characterizing built-environment fuels and susceptibility will refine risk mitigation efforts globally.

Keywords Wildland urban interface · Wildfire · Vulnerability · Structure loss · Mitigation

1 Introduction

Over 38,000 homes and over 200 lives in the US have been lost to just 4 tragic wildfire events since 2018: The Camp Fire (2018), the Marshall Fire (2021), the Lahaina Fires (2023), and the Los Angeles Fires (2025) [1, 2]. US insurance companies have paid over $18 billion in wildfire damages in the 6 years from 2018 to 2023, exclusive of the LA Fires [3, 4], and the broader socioeconomic cost is much greater ($5.5 billion in the 2023 Lahaina

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fires) [5, 6]. Nearly all of these losses occur in areas known as the wildland-urban interface (WUI), where urban environments interface or intermix with natural landscapes [7, 8]. As destructive fires are expected to increase, and as homes continue to be built and rebuilt in wildfire-prone areas, the importance of protecting the WUI is at an historical inflection point [9–11].

Landscape-scale wildfire risk models have been making incremental progress in better characterizing the built environment, but remain focused on hazard and exposure with limited inclusion of individual structure attributes [12–16]. Managing forests for WUI exposure competes with other forest management objectives including timber production [17, 18]. Even if objectives were to be aligned, research indicates that wildfires will continue to burn into the WUI regardless of landscape management efforts [19, 20]. Therefore, focusing on hazard and exposure from natural landscapes without attention to the specific parcel-level features that influence the susceptibility of individual homes is likely insufficient for creating fire-adapted communities [1]. Because a comprehensive definition of wildfire risk entails susceptibility of highly valued resources and assets to wildfire [21], the specific features of individual homes and their surroundings are fundamental to addressing parcel-level risk. Without this component, stakeholders in WUI protection face basic unanswered questions: which people and what assets are the most susceptible to wildfire disasters? What can we do to reduce susceptibility?

Post-fire investigations have sought to answer these questions by analyzing the outcomes of WUI fires. Investigators meticulously survey WUI disaster sites to identify how individual homes ignited and were destroyed or survived [22–24]. These investigations have revealed that structure survival is often related to 'home hardening:' the degree to which a home's construction materials, architecture, and material arrangement prevent penetration by embers and direct flame. In the Lahaina Fires, homes without a Class A rated roof covering were 3x more likely to be destroyed [25]. Survival is also related to a home's 'defensible space:' the features of the environment immediately surrounding the home. In the Lahaina Fires, homes with greater than 60% fuel coverage within 5 ft of the structure were 3x more likely to be destroyed [25]. Home hardening and defensible space are passive fire defense strategies that do not substitute active firefighter intervention, but may lessen the growth rate and intensity of urban conflagrations such that emergent disasters are less overwhelming to active suppression efforts.

The findings of post-fire investigations are pursued in laboratory experimentation. Basic research seeks to measure the heat release rates, ember characteristics, and fire dynamics produced by and received by different WUI materials at various configurations in an effort to better understand structure-to-structure fire spread and develop improved codes and standards for community fire mitigation and structural engineering guidelines [26–34].

The features discovered by post-fire investigations to be important and quantified by their physical properties in laboratory settings have limited presence in open-access structure loss databases [35, 36]. Databases such as CAL FIRE Damage Inspection Data (DINS) [37] are often reported as being limited to California, and are biased towards structure loss without including complimentary information on survived structures or pre-fire conditions. This is noteworthy because statistical analyses often rely on these structure loss databases and other data [36, 38–40]. However, this seems to have improved since the referenced studies were published. The DINS Public View shapefile of the Palisades Fire (2025) includes 6,831 destroyed structures, 4,262 no-damage structures, and 973 damaged structures. For the Eaton Fire (2025), it includes 9,413 destroyed structures, 7,894 no-damage structures, and 1,114 damaged or inaccessible structures. The distribution of structures along a gradient of damage is better for training and testing unbiased descriptive and predictive models of structure loss in California. Because of the different data inputs between empirical and statistical post-fire analyses, the different scales at which risk is assessed, and a lack of information on the physical properties of fuels in the built environment, the responses to the aforementioned questions of WUI stakeholders remain uncertain. These gaps have not been systematically identified in the scientific literature.

To bridge these gaps, standard data-collection methods for characterizing burnable features in the built environment are needed. The use of remote sensing and public property records shows promise in achieving both scalability and data accessibility, enabling computer-driven assessments and urban fuel characterization across entire communities. Scalable and accessible methods are aligned with official recommendations to congress [41]. In the present paper, we identify the current status of methods and models that seek to understand and characterize the wildfire susceptibility of individual homes in the built environment. First, we identify features of individual homes and their surroundings that have been shown to affect structure susceptibility. Second, we review how these features are integrated into whole-home vulnerability indices and assessments. Third, we examine how home susceptibility is incorporated into emerging WUI fire spread models. The intention of this investigation is to provide a common operating picture for researchers developing WUI fuels data for fire modeling and risk assessment, with a broader goal of identifying limitations of current approaches and needs for future ones.

2 Methods

Of the 118 sources that are cited in this review, the majority (over 90%) were published in the last 15 years, with 80 sources published between 2020 and 2025. This recent surge in publications reflects rapid advances in this area, underscoring the need of a comprehensive review to consolidate emerging findings and highlight remaining knowledge gaps. The 118 sources were categorized into 7 groups based on their function and approach (Table 1). While some sources overlapped categories, each was assigned to its primary focus for clarity. Codes/Standards were cited for context and practical guidance on structure and defensible space features. Review/Meta-Analysis, Empirical Evidence, and Simulation Model categories were cited for empirical support of features correlated with structure loss, with Simulation Models also encompassing both structure-to-structure fire propagation and physics-based simulations. Tool/Data Source were cited for their contribution to WUI data

Table 1 Categories of citations

Category	Count
Codes/standards	3
Review/meta-analysis	5
Tool/data source	19
Thematic context/evidence	21
Empirical evidence	22
Simulation model	22
Conceptual/applied framework	26
Grand total	118

acquisition and application. Thematic Context / Evidence supported conceptual arguments and framing. Conceptual/Applied Framework sources introduced or implemented methods of assessing susceptibility and risk in the built environment. With the exception of the Thematic Context / Evidence category, sources were selected for their focus on single-structure characteristics and immediate surroundings, particularly features influencing structure survival or hazardous fire behavior, with priority given to US-based research.

Features of structures and defensible space are not common to different methods of describing or predicting structure susceptibility and structure loss. We therefore categorized features in three groups: (1) Empirical features: Factors found to correlate with structure loss through Review/Meta-Analysis, statistical analysis of damage databases, post-fire observations, or laboratory experiments. These are features that have been observed to correlate with structure loss, and that can describe how variations in each feature, such as the presence or absence of a protective screen on a vent, will influence the susceptibility of a structure to penetration by different fire attack mechanisms. (2) Predictive vulnerability indices: Features included in structure vulnerability assessments (a subset of Conceptual/Applied Framework) designed to predict home survival and help with community wildfire preparedness. These are features that have been incorporated into a method that is designed to be used by either a homeowner or a community to prepare for and/or reduce community-level or single-structure level wildfire susceptibility. Selected models ($n=5$) must produce an index, have published methods, and incorporate parcel-level features. (3) WUI fire spread model inputs: Features used in WUI fire spread models to simulate structure-to-structure fire spread. These features are used to parameterize the susceptibility and the physical fire behavior of individual structures in landscape-scale computer simulations of wildfire in the built environment. Selected models ($n=3$) must be under active use or development and explicitly model structure-to-structure fire spread at the whole-community scale using parcel-level features of the built environment.

Given the extensive research supporting the correlation of empirical features with structure loss, we hypothesized that the most important features that *describe* structure loss would be found in all three categories, including the categories seeking to *predict* structure loss.

Finally, we identified data sources used by researchers to characterize the built environment, evaluating their quality, availability, and application to single-structure feature characterization and loss prediction. While data gaps still need to be filled, these sources provide additional context for characterizing the built environment.

3 Results

The body of literature often interchanges the terms *risk*, *vulnerability*, and *susceptibility*. In this research, we use the definitions provided in the widely-used quantitative wildfire risk assessment framework, where susceptibility describes the expected damage to an asset based on its physical characteristics [13]. Whether a structure is destroyed in an urban conflagration depends on the physical susceptibility of a structure and the intensity and duration of fire and embers it is exposed to [42]. Susceptibility is determined by the characteristics and arrangement of the construction materials of a home that make it more or less prone to ignition. This includes the physical properties of the materials themselves in addition to their size, assembly, and architectural design. Vegetation can be treated to reduce wildfire hazard in a wildland environment while homes and infrastructure are fixed in place, requiring a different approach for mitigating wildfire risk [43]. This approach involves two steps: (1) hardening homes by retrofitting them with less flammable construction materials, or adding protections such as vent screens and non-flammable window shutters [44] and (2) creating defensible space by managing anything burnable within the immediate proximity of the home.

3.1 Empirical Features

At the individual structure level, the features describing structure susceptibility can be parsed into two groups: (1) structure features and (2) defensible space features [45]. These features are used to determine the physical susceptibility of individual structures (Fig. 1).

In this section we describe the features of structures and defensible space that are susceptible to various fire pathways and attack mechanisms where flames and embers may enter a structure. In the text, we highlight some of the more commonly studied features as an introductory overview. Table 2 includes ample citations that contain more comprehensive information including literature reviews, landowner studies, post-fire investigations, statistical analyses, simulations, and homeowner recommendations.

Structure features are components of the home including the roof and windows, as well as the size of the home, the arrangement of the materials, and its architecture style. Structure features are most commonly associated with home hardening actions, which involve using more fire-resistant building materials or adding protections on homes exposed to wildfire. As potential exposure to wildfire increases, home hardening levels should also increase [42].

Windows, vents, chimneys and eaves are common entry points of embers into structure interiors, and common protections include metal mesh screens to prevent ember entry [46]. Windows are particularly vulnerable to direct flame and radiation, which can shatter glass and allow embers and flames to enter the structure envelope [35, 47]. Eaves are also vulnerable to direct flame propagation from below. The choice of building materials used in a structure, and the condition of the materials themselves, may be correlated with structure

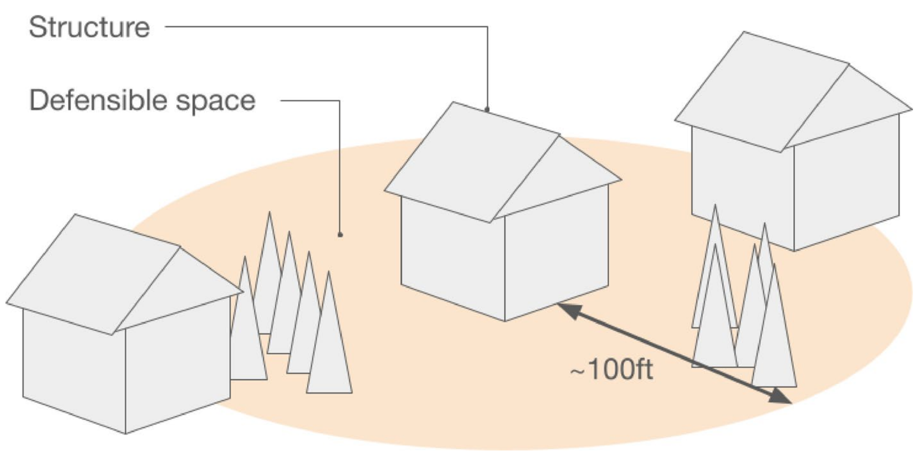

Fig. 1 Conceptual diagram of an individual structure and its defensible space, which may include natural fuels such as trees and artificial fuels such as adjacent homes

Table 2 Features influencing structure vulnerability

Feature	Reference for feature importance and/or recommended practices	Observation type
Structure		
Windows	[24, 36, 38, 39, 44, 48, 49, 55, 56]	A, B, C
Roof material	[36, 38, 40, 42, 44, 48, 49, 55, 56]	A, B, C
Vents	[36, 40, 42, 44, 48, 49, 55, 56]	A, B, C
Eaves	[36, 42, 44, 48, 49, 55, 56]	A, B, C
Siding material	[24, 36, 38–40, 42, 44, 48, 55, 56]	A, B, C
Architecture	[24, 36, 38, 40, 44, 49, 55, 57]	A, B, C
Maintenance	[42, 44, 49]	C
Defensible space		
Artificial fuels	[24, 39, 40, 42, 44, 48, 49, 56, 58]	A, B, C
Landscaping	[22, 24, 40, 42, 44, 49]	A, B, C
Adjacent homes	[8, 22–25, 32, 38, 40, 42, 43, 49, 50, 52, 56, 57, 59]	A, B, C
Canopy cover	[36, 38, 39, 42, 49, 50, 52, 56]	A, B, C, D
Topography	[38, 44, 50, 56, 59]	A, B

4 categories of 'observation type:' (A) post-fire investigation, (B) statistical analysis of damage database, (C) laboratory experimentation, (D) simulation

age, leading to age being a predictive factor of building loss in the Camp Fire [39], Marshall Fire [40], and other California fires [38].

The roof is often the largest area of the home for embers to accumulate and start fires, which may be exacerbated by complex roof architecture, poor roof maintenance, and the accumulation of dead organic matter [44, 48–50]. Statistical analysis suggests that a wooden roof increased the odds of destruction by 539% in the Camp Fire [36].

No single home hardening action is effective in isolation, and home hardening should be addressed systematically. A home is only as strong as its weakest link. Even full-system home hardening does not ensure the survival of a structure exposed to extreme intensities; therefore, reducing exposure is a necessary step in reducing overall risk [25].

Defensible space features are the fuels that exist within a structure's home ignition zone – the area within approximately 100 feet of a structure's outermost walls, according to the National Fire Protection Administration (NFPA) [51]. These features may include artificial fuels such as fences and adjacent homes, and natural fuels such as trees and grass [22, 42]. Treating defensible space with NFPA standards every 10 years can reduce flame lengths by 70% [52]. Fuel load in defensible space was correlated with structure destruction in the Camp, Marshall, and Lahaina Fires [25, 39, 40]. Defensible space is used by regulatory bodies to provide codes, standards, and guidelines for homeowners [51, 53, 54]. Although a homeowner's control over defensible space ends at their property line, fuels beyond the property boundary may still ignite a home especially in dense housing arrangements [42]. Overlapping defensible space is depicted in Fig. 2.

Together, structure features and defensible space features determine a home's susceptibility to wildfire – the likely consequence should a fire reach the home or defensible space either through direct flame, radiation or embers. Table 2 shows a list of features found commonly in the literature along with references justifying the importance of each feature in structure susceptibility and fire dynamics. All studies that observed feature importance can be grouped into 4 categories of 'observation type:' (A) post-fire investigation, (B) statistical analysis of damage database, (C) laboratory experimentation, (D) simulation.

Fig. 2 Clustered houses share defensible space and structures themselves may occupy the defensible space of other structures (Created using ArcGIS software by Esri)

The number of references for each feature in Table 2 does not directly reflect its relative importance to home survivability. For instance, 'Maintenance' is discussed in only three (3) sources, while 'Siding material' appears in ten (10) sources. This discrepancy should not be interpreted as siding material being more critical than the condition of the siding. Instead, it highlights differences in how easily these features can be observed and measured. Siding material, which is often recorded in public property records, visible on both surviving and destroyed structures after a fire, and testable in laboratory settings, is more frequently included in analyses of structure survival. In contrast, maintenance levels constantly fluctuate over time and space and are challenging to evaluate, both before and after a fire, limiting references to studies conducted under controlled, laboratory conditions. Therefore, the features most frequently explored in the literature and included in practical applications are often those that are easier to observe and measure at scale. Other features that can influence susceptibility include skylights, rain gutters, siding patterns, fire-retardant treatments, exterior caulking and sealing, and more [48, 49].

The relative importance of an individual feature is difficult to ascertain for many reasons. Firstly, a small change in any one of the features could result in a structure being destroyed [42]. Secondly, many studies examine feature importance in different geographies, at different scales, using different methods, and answering different questions, making direct comparison challenging or impossible. For example, Syphard et al. [38] found that *local-scale* assessments determined construction materials and defensible space to be more predictive of loss, while *landscape-scale* analysis determined structure density to be more predictive of loss. In Australia, Blanchi et al. [55] examined common entry points of fire to individual structures (e.g. windows, vents, eaves etc.) while Price & Bradstock [59] examined the role of wildlands and structure density while omitting individual structure features, so the relative importance of each is not comparable. Thirdly, post-fire investigations are not always able to determine the exact cause of home ignition. In the Camp Fire, over 40% of surviving but damaged structures showed window damage and over 50% exhibited siding damage [39]. Destroyed structures provide less reliable data for identifying ignition sources. Fourthly, laboratory studies have not replicated the full suite of fuel assemblies and minute structure feature combinations required to unravel the complexity of structure susceptibility and structure-to-structure fire spread.

The set of features in Table 2 may be used to predict the susceptibility of individual homes to wildfire [25]. The standard way that the full suite of features in Table 2 can be collected is through in-person assessments on a home-by-home basis. Researchers have identified that this method is not scalable, and have developed predictive vulnerability assessment methods to address this issue. The term 'vulnerability' is used here in place of 'susceptibility' because some indices include elements of exposure and fire resource response. These vulnerability assessments are discussed in Sect. 3.2.

3.2 Predictive Vulnerability Indices

Whole-home assessment methods integrate and normalize individual features of structures and their surroundings into an index to rate a home's vulnerability. These types of assessments and indices are often used for homeowner education, fire department preparedness, insurance underwriting, policy and standards development, evacuation planning, and community mitigation planning. Depending on the approach, assessment methodologies may assess features at the single-home level, the community level, or both. Table 3 shows the features that are included in five different structure vulnerability assessments and describes how these methods were developed and how the data were collected.

The feature weights are omitted from Table 3 due to the different methods of weighting in each index making comparison challenging. Vulnerability Assessment Tool (VAT) [47] and Physical Vulnerability Index (PVI) [60] both developed models that describe the outcome of a single destructive fire via in-person post-fire assessment. VAT used post-fire analysis in addition to expert fuzzy-logic questionnaires examining various structure features and fire pathways. The logic assigns probabilities of failure of different components of a structure and its defensible space, resulting in a set of weighted, predictive features (Table 3). However, some of the model's features such as vents are difficult to assess without an in-person site visit. Additionally, the index omits the presence or proximity of other structures, a feature well-linked to structure-to-structure fire spread. PVI used Boruta feature selection to analyze post-fire data collected in the field and statistically weight the importance of each feature to home destruction. The primary issue with using post-fire features for pre-fire predictions is that some features from PVI such as distance to burned vegetation cannot be assessed pre-fire. Additionally, other post-fire investigators indicate difficulties in determining the precise pathway by which embers or fire reached and eventually entered a building that has been destroyed. VAT and PVI would both require further validation to be confidently implemented in a predictive capacity by practitioners in other geographies.

The WiRē Rapid Risk Assessment method (WiRē) [61] weighted features depending on the state of each feature. For example, the Ingress/Egress feature receives a score of 0 if there is more than one way in and out of a residence, and 10 if there is only one. Roof mate-

Table 3 Vulnerability assessments

Feature	Source	Data collection method	Model development method
Impact of the main flame front Flash fuels coverage WUI type Complexity of topography Global vegetation continuity Global friction Fire brigade response time Water points Fire breaks Vulnerable infrastructure	Structure Vulnerability Index (SVI; Vacca et al. [62])	Land cover data and local GIS data with local expert consultation required for fire brigade response times	Expert opinion
Roof material Distance to nearest home Defensible space (vegetation) Attachments Defensible space (other combustibles) Siding material Distance to hazardous topography Adjacent fuels Slope Driveway clearance Ingress / Egress Address visibility	WiRē Rapid Risk Assessment (WiRē; Meldrum et al. [61])	Curbside in-person rapid risk assessment	Expert opinion
Roof material Structure type Terrain slope Burnt vegetation Roof (potential leaf accumulation) Type of shutter Main ground covering	Physical Vulnerability Index (PVI; Papathoma-Köhle et al. [60])	Post-fire on-site inspection	Statistical analysis
Roof type Window panes Deck material Eave design Vent screens	Wildfire Resistance Index (WRI for California; Dossi et al. [35])	DINS database	Statistical analysis
Roof material Exterior wall material Shutters Glazing system Roof material Roof maintenance Vents Windows in semi-confined space (SCS) Envelope type in SCS Combustible material in SCS Failure Fuel management	Vulnerability Assessment Tool (VAT; Àgueda et al. [47])	Post-fire site visits and homeowner interviews	Fuzzy logic from expert questionnaire

rial has the strongest possible influence on the overall score, with a score of 300 if wood shake shingles, and 0 otherwise. Weights were determined by expert judgement. WiRē utilizes several features that are not well-linked to WUI fire behavior and home destruction, such as address visibility and driveway clearance. However, these features have a by-proxy effect on suppression efficacy and may provide valuable insights to homeowners and first responders that can help communities prepare for and respond to destructive wildfires. WiRē is the only method of the five to have compared a priori vulnerability assessments to the outcome of a destructive fire [61]. The WiRē method involves drive-by assessments of homes, and the results of their post-fire analysis indicate that a home is more likely to be destroyed if its features cannot be assessed from a vehicle. This conclusion warrants clarification and further validation. The use of a rapid drive-by risk assessment greatly increases the pace and scale at which home assessments can be made, compared to more rigorous in-person assessments.

The Structure Vulnerability Index (SVI) [62] and Wildfire Resistance Index (WRI) [35] are the only two methods that obtained data from open sources not requiring in-person site visits. WRI uses the features included in the DINS database for validation purposes. Weights were equal among variables, but analysis was later performed to determine feature importance by comparing Cramèr's V, Bayes Factor, and Boruta feature selection, which disagreed on relative feature importance. DINS is weighted towards destroyed structures rather than survived structures, leading to model bias and challenges in validation [35]. The structure features obtained from DINS for WRI were roof material, window panes, exterior wall material, deck material, eave enclosures, and vent screens. Additional research indicates that DINS can be combined with California's Defensible Space database to obtain more attributes and a better balance between destroyed and damaged structures, albeit a smaller dataset [36].

There is not one feature that is used by all five assessment methodologies. The most common structure feature is the roof material, used by four of the five models. VAT and WRI classify roof material as either combustible or non-combustible. WiRē classifies roof material into two categories, one of which includes tile, metal, or asphalt shingles, and the other which includes wood shake shingles. PVI has five classes of roof material ranging from "concrete slab with tiles" (least flammable) to "wooden roof with metal tiles" (most flammable). The weight assigned to roof material differs among models.

The differences in roof material classification between these models demonstrate how localized these methods are. Localized fuel models may be necessary for prediction because of regional differences in housing construction materials, defensible space, road networks, and surrounding wildlands [38, 60], and because the insights from these assessments are intended to be applied at the local level.

SVI differs from the other 4 modes in that it incorporates features primarily at the WUI mesoscale, resulting in a whole-community assessment methodology that predicts where and how a wildland fire might become established in a community or neighborhood. Although parcel-level attributes have limited inclusion in SVI, the mesoscale approach is conceptually similar to explicitly modeling wildfire spread in the built environment (discussed in Sect. 3.3). WUI conflagrations are often carried by both structures and vegetation; capturing this interaction at both the single-structure and the community level is necessary for predicting structural damage [63]. Single-structure features are important because the disaster sequence may be interrupted by homes that are able to survive without firefighter protection [64]. Therefore, because a vulnerability index is a summary of the home's levels of home hardening and the maintenance of defensible space, vulnerability indices may be predictive of a structure's role in whole-community disaster sequences.

3.3 WUI Fire Spread Model Inputs

Forests and grasslands can often be represented in wildland fire spread models as relatively homogenous fuelscapes. In contrast, the WUI presents a complex mosaic of structures, vegetation, and non-burnable surfaces, requiring a more detailed understanding of fuels and physical processes to accurately model fire pathways [65, 66]. In Sect. 3.1, we described the features of structures and defensible space that are susceptible to various fire pathways and attack mechanisms where flames and embers may enter a structure. In Sect. 3.2, we examined features of structures and defensible space that have been used to develop risk indices that predict parcel- and community-level structure loss. Here, we examine the role that these features play in the emerging field of structure-to-structure fire spread modeling. Currently, three primary WUI fire spread models are actively discussed in the scientific literature and remain under ongoing development: M1 [67], M2 [68], and M3 [69]. Additional models have contributed to the field but do not appear to be actively maintained [70, 71]. In this section, we provide a brief overview of M1, M2, and M3 with specific focus on the degree to which features of structures and defensible space ('fuel features') are incorporated into simulated fire spread mechanisms.

M1, M2 and M3 perform sequences of susceptibility, ignition, and hazard on structures and vegetation through physical proxies. These models have been validated retrospectively against urban conflagration events such as the Marshall Fire where success is evaluated by rate of spread and agreement of structure loss patterns [73, 78]. M1 quantifies community vulnerability by applying a graph model of wildfire inside a community. The directed graph incorporates different propagation modes that move across a community via ways - which represent different fuel classes such as 'structure' and 'vegetation' - and nodes which represent components of each way. Fire propagation occurs along edges between nodes, which can include both internal propagation (fire spread within a fuel object) or external propagation (fire spread between fuel objects). The probability of fire spread between nodes is dependent on wind and specific structure features which the modelers maintain influence ember production and heat release rate. The susceptibility of a way is described as the probability of a fire reaching it. M2 uses cellular automata to spread fire on a grid-representation of a community, where each 30 m cell is a structure, vegetation, or non-burnable. M2 includes a time-step component in which a burning cell takes on three values across time: ignition, fully-developed with contribution to spread, and burnt. In each stage of fire development, a cell produces different rates of thermal output, flame, and embers, which are modified by a wind parameter. Adjacent and nearby cells can be ignited by flame and embers according to certain thresholds. M3 is a semi-physical, 2D representation of fire spread in a community. It includes time-stepped fire spread through embers, direct flame, and radiation, where each fuel object has different probabilities of ignition through time and space according to its distance to burning objects, the heat and ember release rates of those objects, the direction and velocity of wind, and the combustible fraction (susceptibility) of the target object. Table 4 describes the structure features used in each model. All three models and the research and data that support them are in active development, and the current state of the models is likely beyond what is reported here. Since initial publication, additional papers have been released for M1 [63, 72, 73], M2 [74–78] and M3 [79].

All three models parameterize the physics of fire spread and are therefore theoretically capable of capturing interactions of detailed features of the built environment across relatively large geographies (i.e. whole-community). Compared to process-based computational fluid dynamics (CFD) models that represent complex and interactive physical fire processes [33, 80–84], current WUI fire spread models are simpler, more computationally efficient, and run in larger spatial domains [74]. The larger domain requires community fuel attributes to be simplified. To obtain simplified proxies in a way that makes WUI fire spread models predictive, the specific features of structures and defensible space that influence susceptibility and fire behavior should be attributed to the network of fire spread; however, such urban fuel models have not been developed, and methods for collecting such datasets were not found in this review. Table 4 lists the features that are used by M1, M2, and M3 to characterize WUI fuels.

The primary structure and defensible space features that determine WUI fire spread in these models are related to the size of structures and vegetation. All three models in some way use the unit area/volume of a home and/or vegetation to determine its heat and ember outputs and/or its likelihood of ignition. In the state of the models as we reviewed them, structures and vegetation generally have constant heat and ember outputs, and constant heat and ember thresholds for ignition. However, we know from structure susceptibility research that these constants should vary among individual homes depending on the features of each structure and defensible space. The features identified in Sect. 3.1 are apparently absent from WUI fire spread models. Analysis of WUI fire spread models would suggest that the

Table 4 Fuel features determining structure vulnerability in WUI fire spread models

Fuel type	Feature	Characterization
M1 [67]		
Structure	Material	Constant: wood
	Size	3 values: 100, 150, 200 m^3
	Probability of ember access	0.90
	Probability of ignition by direct flame	Ignites if touched, unless intervention strength is applied (e.g., 70% hardening)
Vegetation	Probability of ember access	1.0
M2 [68]		
Structure	Volume	Constant: assumes stereotype building ($10m^3$)
	Ignitability	Ignitable by radiation (constant critical heat threshold) and embers (constant ember accumulation threshold)
Vegetation	Volume	Constant: assumes full coverage of cell by douglas-fire trees
	Ignitability	Ignitable by embers (constant ember accumulation threshold)
M3 [69]		
Structure	Size	Area of roof
	Material	Combustible fraction 0.1–1 where all-wood = 1
Vegetation	Size	Area

size of a structure or vegetation object is the *most* predictive feature of susceptibility to ignition. This finding is not confirmed by the research from which the empirical features were derived, and suggests that improved parameterization of structure and defensible space features would assist WUI fire spread models in representing structure susceptibility.

It is notable that structure and defensible space features may not be directly applicable to WUI fire spread models, presently. For instance, M1 incorporates structure modifications by applying a global hardening variable (e.g., 70% hardened) uniformly across all structures in the model domain. While this may reduce modeled fire spread, it is difficult to relate '70% hardening' to actions taken by homeowners, insurance, or communities. M2 uses volume of vegetation and structures to simulate fire outputs, suggesting this model may benefit from 3D characterization of vegetation cells with remote sensing, and basic information obtained from a structure's property records such as structure area, number of floors, and/or number of rooms (Sect. 4.1). M3 adjusts the home's combustibility using a combustible fraction tied to building materials. This model excels in its use of basic research in the parameters that influence heat release rates, ember outputs, and structure ignition thresholds. This suggests more fuel attribute information such as vegetation density and building materials may increase model accuracy by adjusting the fire transfer coefficient and the heat flux required for ignition. However, it remains unclear from the reports whether detailed structure and defensible space attributes can feasibly be incorporated into M1, M2, or M3 at the parcel level.

Even with detailed fuel attributes, further research is still needed to determine the ignitability, heat release rates, and ember production of different materials and configurations. These insights are essential to evaluate how changes to WUI fuel attributes affect broader-scale home and community susceptibility [23, 74]. Research on the physical processes of structure-to-structure fire spread is ongoing due to the challenges of field observation and laboratory replication (e.g [85]). , . Extensive combinations of specific building materials and their arrangement pose challenges to measuring the heat outputs and ignition thresholds, even in controlled laboratory environments. Until such research is more complete, WUI fire spread models will not have the foundational knowledge required to translate detailed fuel attribute information to model accuracy.

4 Discussion

4.1 Data Sources for Structure Susceptibility

Important considerations when using structure features in models and indices that describe or predict structure loss include availability, granularity, utility, and scale. The data sources that were used by many of the studies we reviewed exhibit tradeoffs across these four dimensions. In this section, we identify selected open data sources that have been used by studies to characterize parcel-level features that describe or predict structure loss. We briefly describe the contents of the data sources, identify limitations, and cite studies that used these databases for risk assessment or prediction, where applicable. By compiling these data sources in one location, we open the conversation for researchers to advance structure-level assessments using open data and standard methods.

The literature is replete with data sources and methods for overcoming challenges related to measuring structure-level attributes. Companies such as First Street have used property records from companies such as LightBox who sell nationwide tax assessment data, but the completeness of these data is reported to be inconsistent [86]. Databases such as USA Structures [87], National Structure Inventory [88], and the Historical Settlement Dataset [89] contain nationwide structure attributes with less detail than tax assessments, but may be suitable for research requiring less single-structure detail and greater scale of application. An underutilized source of structure features in the US is the local county tax assessor, which only appeared in one study [39]. Tax assessor records are likely available from a county office for every commercial and residential structure in the county. The content of each county database differs. In the authors' experience of Montana and Colorado county tax assessments, a county database of structure attributes commonly includes structure square footage, lot size, year built, condition, roof material, roof structure, architecture type, attached/detached garage or outbuilding, number of rooms, siding material, and more. Similar features were found in county tax assessor data in California [39].

Some datasets characterize structure attributes at a coarser scale. The SILVIS Global WUI database provides information on housing density and vegetation type and has been used in regional risk analyses [8, 90, 91]. This dataset contains classified land types of both intermix and interface WUI types combined with vegetation data. This is a useful classification for describing building exposure because up to 97% of structure loss may occur in areas designated WUI [8, 92]. The National Land Cover Database [93] has also been used to simulate WUI fires for vegetation and structure land cover types [94].

Studies commonly use Microsoft Building Footprints to obtain structure locations, but there are known commission and omission errors in this dataset and it may require manual cleaning [16, 63, 95–98]. At least one study used Google Street View to obtain empirical information on structures following the Marshall Fire [40]. Additional computer vision and machine learning techniques are sure to add to the growing body of direct or indirect measurement of useful structural data [99].

Because of the complex nature of WUI fuels and the need to characterize thousands of structures for a single community, remote sensing and the use of these databases offers a more scalable alternative to in-person assessments [100]. Airborne light detection and ranging (LiDAR) – a method that uses lasers to measure distance from the sensor to a target object [101] – has been improving roof characterization [102] and vegetation characterization [103]. Airborne LiDAR data are increasingly available for broad areas such as Colorado, unlocking new methods for open-access WUI characterization [104]. Roof characterization with remote sensing is a rapidly developing field and an excellent case for computer vision. Techniques and training databases for roof segmentation and characterization models are documented in deep learning literature [105–108] including the xBD dataset for global damage assessment [109].

Remote sensing and property records are unlikely to provide real-time information on every feature of a structure, especially ephemeral attributes such as cleanliness of rain gutters and presence of lawn furniture or automobiles. However, it provides a foundation for consistent, scalable data that can be obtained for communities nationwide. Table 5 presents a suggested dataset containing features that meet four criteria: they are empirically linked to structure loss and/or WUI fire spread model parameters, their measurements can be obtained for single structures, they can be obtained at a county-wide scale, and charac-

Table 5 Features measurable without in-person assessment

Variable	Data source	Characterization method
Structure		
Roof material [61]	County tax assessor	Empirical
Roof area (m^2) [69]	Satellite imagery	Raster calculations
Siding material [61]	County tax assessor	Empirical
Volume of home (m^3) [68]	LiDAR-derived rasters	Raster calculations
Complexity of roof shape (1–5) [60]	Satellite imagery	Computer vision
Defensible space		
Presence of deck [35, 40]	County tax assessor	Empirical
Distance to nearest structure [42]	Building footprint geometries	GIS
Number of adjacent homes within defensible space [42]	Building footprint geometries	GIS
Presence of outbuilding [42]	County tax assessor	Empirical
Volume of vegetation within defensible space [68]	LiDAR-derived rasters	Raster calculations
Distribution of fuels within defensible space [52]	LiDAR-derived rasters or satellite imagery	Raster calculations
Slope [44]	LiDAR-derived digital elevation model raster (DEM)	Raster calculations
Exposure		
WUI class [8]	SILVIS Global WUI	GIS

terization does not require in-person assessment. The features that are missing from Table 5 but are included in Table 2 (empirical features) include windows, vents, and eaves, which are difficult to characterize without in-person assessments and are not apparent in tax assessment data or other widely-available data sources.

4.2 Key Findings and Gap Analysis

In the present review, we identified three methods of describing and predicting structure vulnerability and structure loss: empirical features, predictive vulnerability indices, and WUI fire spread model inputs. The primary gap identified is that the features that are used in each of these methods differ, as do the methods to characterize each feature, and the way that each feature is incorporated into predictive models and indices.

At least 12 features of structures and defensible space (Table 2) are commonly cited in the literature and have been empirically linked to structure loss via post-fire investigation, statistical analysis of damage databases, and laboratory experimentation. Each of these features can be further characterized by nuanced attributes. For example, windows can be single- or double-paned (or more), may be protected by flammable or non-flammable shutters, be made of tempered or non-tempered glass, and come in a variety of shapes, sizes, arrangements, and exposure to adjacent flammable materials. This makes structure attributes and the flame and ember behavior associated with each feature configuration highly stochastic and difficult to represent in WUI fuel attribute models. Our review of empirical features in Sect. 3.1 demonstrated that flames and embers may enter structures and defensible space through any of the 12 features. Home hardening and defensible space should, thus, be taken as a whole-system approach at the structure and community levels. This is because a structure is only as resilient as its weakest link: a home may have a non-combustible roof but embers may still enter an attic space through vents if they are not protected with metal mesh screens. For a whole-system approach to home hardening and defensible space, the National Institute for Standards and Technology (NIST) has developed rigorous guidelines for the implementation of hazard reduction at the parcel level [42].

The only feature that was included in empirical features and every predictive model and index we presented (with the exception of the community-level SVI) is the roof. This was described and weighted differently among predictive models and indices, descriptions ranging from roof material and architectural complexity to simple assessments of roof area. These inconsistencies make it difficult to determine whether the roof is the most important driver of structure loss, or whether its inclusion reflects assumptions, practicality of observing the feature, or conventional emphasis rather than empirical importance. To illustrate this point, three of the vulnerability indices (WiRe, PVI, and VAT) used data that could be collected in-person via drive-by assessment, post-fire assessment, and pre-fire assessment, respectively. While many of the features used by these three indices are empirical features correlated with structure loss, the inclusion of features in each model was limited by the features that were able to be collected. Another vulnerability index, WRI, uses detailed structure-level data from the DINS database. Features from WRI such as windows, vent screens, and eave design are difficult to characterize without in-person assessments, as discussed in Sect. 4.1. Without in-person assessments, the observable features of structures and defensible space are largely limited to what can be obtained from property records and remote sensing, as discussed in Sect. 4.1.

In addition to features derived from different data, the weight given to these features is dependent on the method that was used to assign weights. For example, PVI used Boruta feature selection applied to data collected post-fire in a single community following a single destructive fire. WRI weighted attributes from the DINS database which was reported to be skewed towards destroyed rather than survived structures at the time of the analysis. VAT used fuzzy logic from questionnaires completed by experts and applied it to features that were collected in-person for a local area. Feature weights are expected to differ between locations [62]; however, using different features makes comparison of these weights unattainable. Research is not easily replicated or validated as a result.

In Sect. 3.3, we reviewed the WUI fuel attributes used by WUI fire spread models to model fire spread in the built environment. The ability of these three models to characterize features of structures and defensible space is limited primarily by the lack of basic research on the fire and ember characteristics associated with structure materials and configurations. However, the model parameters identified in Table 4 suggest that M1 could be improved with the characterization of home hardening levels on individual structures, M2 could be improved with the characterization of individual structure size and the volume/arrangement of vegetation in vegetation cells, and M3 could be improved with the characterization of the combustible fraction of construction materials on individual structures. Such characterization can be achieved through property records and remote sensing techniques outlined in Sect. 4.1, but further basic research is required to make these characteristics beneficial to the models. Specific research needs are discussed below.

5 Conclusion

Consistent WUI fuel attribute datasets will benefit multiple research areas and applications, but only if researchers work across disciplines to fill this gap. It will require integrating the features found in each of the three groups: empirical features, predictive vulnerability indices, and WUI fire spread model inputs. To this end, the research community should aspire to a standard set of single-structure and defensible space features that are linked to empirical features, can be collected pre-fire for entire communities nationwide, and do not require in-person site assessments for every structure. Developing such feature sets will unlock replicable and insightful research that bridges disciplines and better serves fire managers and homeowners.

The existence of such feature sets is, so far, not evident. Neither are methods to develop standardized datasets, nor codes and standards for such datasets. The absence of these feature sets underpins several research gaps including validating susceptibility and WUI fire spread predictions, covering large geographic regions with single-structure susceptibility data obtained pre-fire, and understanding how to weight features in local-scale susceptibility and WUI fire spread predictions.

When a set of features is determined, predictive WUI fire spread models and susceptibility indices should begin to utilize features of the built environment at single-structure resolution that can be obtained without in-person site visits and are well-linked to descriptive features. Models seeking to make local predictions should be developed at local scales, as encouraged by several authors (e.g [35, 43, 60]). More broadly, fuel attribute datasets should be produced *pre-fire*. Empirical feature characterization following urban conflagrations will benefit predictive model development if standard features are characterized pre-fire rather than solely retrospectively. A suggestion for a dataset that meets these requirements is presented in Sect. 4.1.

Basic research on fire behavior properties such as the heat release rates and ember production of specific materials is a parallel research gap to WUI feature datasets. It is currently a significant limiting factor on the representation of WUI fire spread at scale. The gap between basic research and WUI fire spread models could be reduced if basic research measured fire behavior properties in whole-home and whole-community combustion experiments in addition to single-object experimentation. However, there are significant barriers to conducting such experiments due to the stochasticity of material arrangements within structures and structure arrangements within communities, and the physical and logistical scales of such experiments.

This paper has reviewed knowledge and methods related to standardizing and scaling *passive* wildfire defense strategies that use home hardening and defensible space to reduce the likelihood of structure-to-structure fire spread in a community. However, *active* suppression may be the most important determinant of structure survival [71]. In California fires, over 90% of structures that were damaged but not destroyed were defended by firefighters [42]. Measuring suppression effectiveness is challenging because suppression happens during emergent situations in which life and property take priority over research. Characterizing the effects of direct suppression on structure loss can improve firefighter response, WUI fire spread modeling, and risk mitigation effectiveness [38, 45, 57].

Because the WUI is the intersection of the built and the natural environment, it presents issues across social, economic, engineering, physics, and ecological domains. The WUI therefore provides a common ground for diverse areas of study to address a large issue from different angles. Researchers should look to urban fuel classification as an area of research that can fill gaps in structure susceptibility prediction. Just as standard fuel models have benefited wildland fire spread models (e.g. Scott and Burgan's 40 fire behavior fuel models [110]), fuel models for the built environment may provide forward momentum to future structure-to-structure spread, structure susceptibility, and community vulnerability predictions. The 40 fire behavior fuel models connect fire behavior to certain fuel archetypes. Fuel archetypes in the built environment, characterized solely by structure loss likelihood, are presumed to be achievable given the current state of research and data availability. However, significant advances in laboratory experiments and detailed observations of active urban conflagrations would be required to characterize archetypes by fire behavior under varying weather and topographical conditions. Another application of *physical* vulnerability prediction is improved community- and national-level understanding of *socioeconomic* vulnerability, another promising area for future research [6, 111–118]. Physical susceptibility of structures and communities is the foundation from which the WUI problem must be addressed [1], and there is an increasingly urgent need for progress in this field.

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Declarations

Conflict of Interest The authors declare no competing interests.

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