A Network Approach to Mapping Responsibility in Wildfire Risk Mitigation

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ABSTRACT

As wildfire risk escalates in the wildland urban interface/intermix (WUI), creating defensible space clear of flammable fuels is important for wildfire risk mitigation and management. By definition, defensible space is constrained to the property parcel's boundaries and wildfire risk assessments generally focus on individual parcels, but this overlooks any risk in neighboring properties. If we imagine defensible spaces as buffers that cross property boundaries and overlap, neighboring properties may share wildfire risk in the overlapping regions. However, homeowners may not be able to recognize these overlapping regions and spillover effects of mitigating risk, which leaves properties and the entire neighborhood vulnerable to wildfire risk. To address this issue, we propose a novel paradigm to rethink defensible spaces by measuring the homeowner's responsibility to mitigate wildfire risk in overlapping defensible space buffers, which can be shared and owed between neighbors. First, we develop three new spatial metrics (Personal Responsibility (PR), Shared Responsibility (SR), and Owed Responsibility (OR)), computed as the product of wildfire risk contained in the homeowner's region of responsibility. Second, we build spatial responsibility networks, modeled using all the houses in a given neighborhood by building spatial networks with nodes characterized by average PR and links weighted by either average SR or OR with directions that designate who is responsible. In our study site, we find that SR networks exhibit sub-networks while OR networks emerge as high-risk clusters. This information is important to inform homeowners about their individual responsibilities, identify properties at higher risk, and gather neighbors with interconnected responsibility. Subsequently, we simulate different mitigation strategies by iteratively removing network links and monitoring how the total responsibility may change in the neighborhood. We use three strategies (random, localized, and targeted) for link removal. Results demonstrate that the targeted strategy (removing links in descending order of highest responsibility) reduces the total responsibility most rapidly and fragments the network into smaller components, thereby reducing overall wildfire risk in the neighborhood. Through this study, we provide a framework for wildfire risk management, which can be used universally with different risk metrics and for different neighborhood layouts. Ultimately, the spatial responsibility metrics and networks provide a scalable and spatially-explicit approach to map complex wildfire risk in the WUI, which can help inform defensible space inspections, guide efficient resource allocation, improve neighborhood-level planning, and empower individual homeowners to make more risk-informed decisions.

1. Introduction

The Wildland Urban Interface/Intermix (WUI) is a heterogeneous landscape where buildings and wildland vegetation meet or intermingle, with varying land use and public/private jurisdiction zones [1–6]. The WUI is also a complex nexus of anthropogenic and natural processes where lives, infrastructure, and communities are often most vulnerable to wildfire [7–10] due to the growing population density and accumulation of flammable fuels in recent years [3, 4, 6]. Wildfire risk management is, therefore, an urgent priority in the face of mounting risk of catastrophic wildfire damage as well as escalating fire suppression and insurance costs [11–13]. To reduce wildfire risk, mitigation is needed at multiple scales [8, 14]. Regional-scale policies alter forest structure and reduce fuel continuity to decrease the intensity and spread of fires through prescribed burns, mechanical thinning, and fuel breaks. Local-scale policies focus

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at the parcel level, where risk mitigation is governed by local governments and individual homeowners. Mitigation measures include home hardening (i.e., retrofitting with fire-resistant materials) and maintaining defensible spaces by clearing flammable fuels around structures [15].

Defensible spaces are widely-accepted as a cost-effective and practical strategy for protecting structures in the WUI from wildfires [15–20]. This strategy consists of treating, reducing, or clearing flammable vegetation and other combustible material around structures to reduce the likelihood of fire transmission [17]. Defensible space regulations vary by state and country [20]. For instance, for designated fire hazard severity zones in California, homeowners need to maintain defensible space in zones ranging from 0-5 ft, 5-30 ft, and 30-100 ft from structures (Public Law Code: CA PRC 4291). In the literature, studies have reported mixed results on the effects of fuel mitigation on building survivability [17–19, 21, 22]. Yet structural separation distance (SSD) has often been recognized as a critical factor in determining the likelihood a structure survives in a wildfire [15, 23, 24]. In particular, Zamanialaei et al. [24] showed that changes to the building structure and its surrounding fuels in the home ignition zone (0-5 ft) can yield the most improvement in reducing structural losses. Consequently, there is a push towards maintaining defensible spaces to reduce wildfire risk and create a safer space for firefighters [17, 25].

By definition, defensible spaces are constrained within their property lines [20, 26]; however, fire will spread continuously without considering such boundaries. If defensible space boundaries were to extend beyond property lines (i.e., defensible space *buffers*), there may be overlapping spaces where unmitigated fuels or flammable hazards would increase the risk of fire spreading to neighboring houses [17, 22, 27, 28]. Given the growing density of the WUI [3, 4, 6], wildfire risk in these spaces, especially if left unattended, presents a significant concern that needs to be identified and managed.

Risk externalities can exist in these overlapping areas, where the presence of wildfire risk in one's defensible space can impact the risk in neighboring properties. In the economics literature, spatial econometric and game theoretic models are used to investigate risk externality by representing how the decision to create defensible space leads to potential spillover benefits for neighboring properties [13]. Notably, Shafran [29]'s theoretical model predicted the relationship between one's choice to create defensible space and the resulting decision of neighboring properties. Their model found that the benefit of creating defensible spaces for private landowners is dependent on their neighbors' decision. Further, empirical data from home assessments by wildfire professionals have been used with spatial lag models to present defensible space as a strategic complement (i.e, mutually reinforcing) [29, 30], suggesting that a homeowner is more likely to mitigate if their neighbor has already mitigated [13]. This model's results are corroborated by a survey of homeowner opinions on wildfire risk mitigation by Brenkert-Smith et al. [31], which found that creating defensible space is of little value if neighboring properties are untreated. In other words, even if the majority of homeowners create fire-proof defensible spaces, the non-compliance of a single neighbor (i.e., "free-riding" behavior) can jeopardize the safety of the entire neighborhood if their unattended hazard ignites and leads to fire spread [32]. Extending this further, Shafran [29]'s model has also considered social norms [33], since one's decision to mitigate can be influenced by social interactions and external social factors [31, 34]. Factors such as social norms and spatial proximity to neighboring properties can affect risk perception and human behavior when considering whether to mitigate in defensible spaces [30, 31, 33–39].

A critical gap is that these econometric models do not produce spatially-explicit or geographic information [13, 29, 30, 33, 36]. In contrast, the fire ecology and science literature uses spatially-explicit wildfire risk maps (e.g., wildfire hazard potential, ignition potential, burn probability or wildfire likelihood based on fire spread simulations, expected fire behavior, etc.) [1, 6, 40, 41], but does not acknowledge complex risks like spatial spillovers. Bridging these fields together would provide a nuanced understanding of multi-parcel risk and granular information at the individual property level, thereby empowering stakeholders at multiple scales such as public/private landowners, local governments, and state/federal policymakers. Recent studies have focused on assessing wildfire risk at the parcel-level to examine for spatial spillover effects [42, 43]. In particular, Pludow and Murray [43] presented a spatial optimization approach to investigate spatial spillover benefits from wildfire treatments given budget constraints. However, the study computed relative risk scores for each parcel without explicitly considering spatial properties and the spatial spillover effects only considered the four adjacent neighbors. To advance these works, a spatial "systems view" is crucial which considers spatial spillover effects but also provides spatially-explicit information at the individual property level. One concern is the coarse resolution of open-source wildfire risk maps, which are typically disseminated at up to 30-m spatial resolution [41]. While these risk maps are useful, they may not provide sufficiently granular information to resolve risk information at the individual property level (e.g., one pixel may cover multiple properties) [41]. Since the decision to mitigate occurs at each property, homeowners would need sub-parcel scale information to assess property risk as well as to determine their role and contribution in risk mitigation. Given fine-scaled information, we need multi-parcel risk assessments to map and understand mutually shared risk. Norton [44] analyzed multi-parcel risk during the 2018 Woolsey Fire by spatially overlaying 100-ft defensible space buffers and classifying the overlapping spaces into critical zones (mutual risk, isolated risk, and excluded risk). A high resolution wildfire risk map was then used to indicate regions that exceeded a high-risk threshold (red-flag weather conditions). While this approach can spatially map multi-parcel risk, it does not quantify the share of risk at the individual property level. This level of information is critical to understand interconnected risk between neighbors and the required contribution of each homeowner.

In response to the aforementioned limitations, we propose a framework to re-imagine defensible space as potential opportunities for homeowners to identify interdependent areas and mitigate mutual risk between neighbors. We first propose a shift in the analytical focus from *risk* to *responsibility*. Borrowing from risk theory [45, 46], responsibility is the notion that certain entities may have an obligation to undertake actions to manage risk and accept consequences for the outcome [47]. This shift from *passive* risk assessment to *active* accountability facilitates the identification of *who* holds responsibility and *to what extent*. Such a perspective not only advances theoretical understanding but also holds practical implications for enhancing and mobilizing community-wide mitigation. These advances can then help to inform policy design, foster a sense of stewardship, enable targeted engagement, and support the development of resilient, fire-adapted WUI communities capable of co-existing with wildfire in today's era of extremes [8, 48, 49]. Using this framing, we highlight three main contributions in this paper:

- **Multi-parcel risk assessment using spatial metrics of responsibility**: We re-imagine defensible space (similar to previous studies [22, 27, 28]) and propose novel spatial metrics (personal, shared, and owed responsibility) that characterize the homeowner's responsibility to mitigate risks on their property relative to their neighbors.
- **Building spatial networks of responsibility**: We represent each spatial responsibility metrics as a directed spatial network with nodes weighted by personal responsibility (PR), and links represented by shared responsibility (SR) or owed responsibility (OR) between neighboring properties.
- **Network-based simulation of risk mitigation strategies**: We create three strategies for risk mitigation and implement them on the SR and OR networks via network link removal to monitor how responsibility of risk mitigation changes across the entire neighborhood.

2. Methods

2.1. Wildfire risk from fire spread simulations

We generate a demonstration study site that is characteristic of a WUI neighborhood with 70 houses (building footprints) with an average SSD of 8.57 m, as shown in Fig. 1. The study site is important to illustrate how to apply our proposed spatial metrics and construct spatial responsibility networks. We also used 109 parcels with an average area of 1205.14 m^2. We first generate a fuel map, assuming a "worst-case scenario" where all houses are burnable and are modified as fuel model SB4 (high-load blowdown) from Scott and Burgan [50]. We also assume properties are filled with SH7 (very-high load shrub and litter) and GS2 (moderate-load grass-shrub) fuels. We created a synthetic digital elevation model for this same area and computed slope and aspect. We also created a canopy cover map (ranging from 0 to 100%). All inputs are matched to 1 meter spatial resolution. We then use FlamMap [40] to simulate wildfire behavior, using a wind speed of 25 mph blowing uphill with 75% foliar moisture. We also assume a moderately dry fuel moisture content scenario [50]. From the FlamMap outputs, we use rate of spread (ROS) [ft/min] as a proxy for wildfire risk.

2.2. Spatial responsibility metrics

We redefine the defensible space as buffered areas of 30 ft radiating from the homeowner's structure(s), which may extend beyond the property line. The 30 ft buffer corresponds to Zone 1 requirements in CA PRC 4291 for those living in the State Responsibility Area or Very High Fire Hazard Severity Zone in the Local Responsibility Area in California. We focus on this regulation assuming that 30 ft is a safe estimate of a buffer for properties in Zone 1. To note, the proposed metrics are agnostic to the defensible space's buffer size, so that they can be applied *universally* to other distances as well. For parcels with multiple structures (e.g., alternative dwelling units, sheds, etc.), we merged their defensible space buffers together to ensure a "many-to-one" mapping of buildings to property parcel. Using the defensible space buffers and the parcel polygons, we introduce three novel spatial metrics to measure the homeowner's

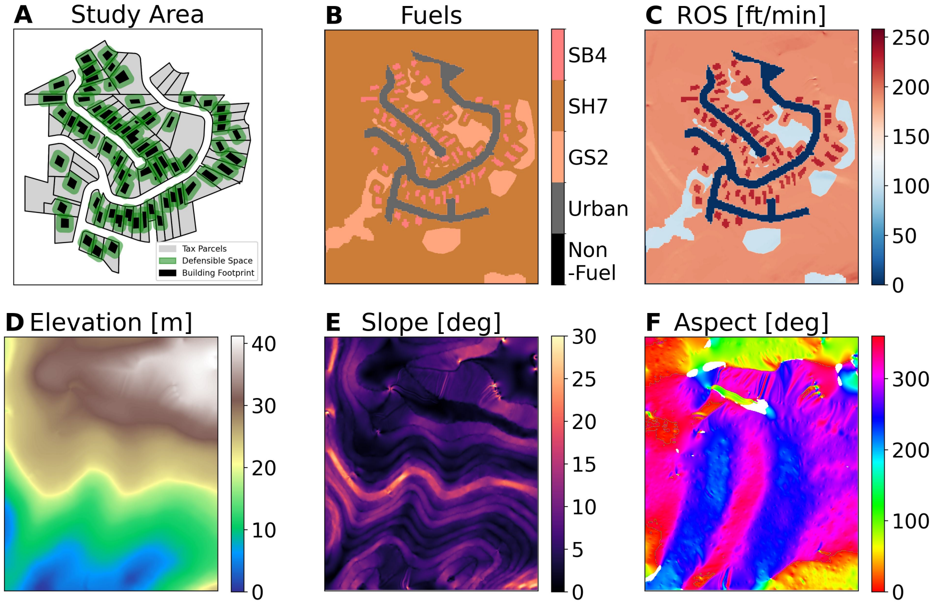

Figure 1: Map of neighborhood and input data used for fire spread simulation. **(A)** Study area shown with 70 buildings, property parcels, and defensible spaces (30-ft buffers), **(B)** input fuel map based on 40 fuel model classification [50], **(C)** rate of spread (ROS) [ft/min] from FlamMap used as a proxy for wildfire risk in our study, **(D-F)** topography inputs including elevation [m], slope [degrees], and aspect [degrees].

responsibility to mitigate fuels in their defensible spaces: SR, OR, and PR (See Figure 2 for a visual diagram of each metric). The defensible space buffers are shown to be circular in the figure for demonstration purposes; however, the actual defensible spaces are likely more irregular and complex. SR is described as the average risk in the area of overlapping defensible space buffers; OR is described as the average risk in the area of a given homeowner's defensible space buffer which overlaps *only* with the neighbor's parcel, but not with their neighbor's defensible space buffer; and PR is described as the average risk in the defensible space of homeowner within their own parcel and excludes any SR and OR regions from neighboring properties.

Formally, we define three spatial responsibility metrics (PR, SR, OR) to represent how one's defensible space overlaps with their neighboring parcels. We also include directional indexing to specify who is responsible to whom for risk in the overlapping area. Let $\mathcal{H} = \{h_1, h_2, \dots, h_n\}$ denote the set of n houses in a given WUI neighborhood. Suppose we label the house of interest as i and a neighboring house as j, where $i, j \in \{1, \dots, n\}$ and $i \neq j$. Each parcel is denoted by $t_i \subset \mathbb{R}^2$ (parcel boundary of house h_i). Each house generates a defensible space as $D_i \subset \mathbb{R}^2$. If there are m distinct defensible-space buffers from multiple structures on t_i, they are combined by union: $D_i = \bigcup_{k=1}^{m} D_{ik}$. Each metric is computed as the product of the area of the relevant region as $Area(\cdot)$ and the average risk over that region as $\bar{r}$. The three spatial responsibility metrics are then expressed as follows:

- **Personal Responsibility (PR$_i$)**: For a given homeowner (h_i), this is the risk over the region of D_i that lies within their own parcel t_i and excludes any overlapping defensible space buffers from neighboring properties:

$$\mathrm{PR}_i = Area\Big((D_i \cap t_i) \setminus \bigcup_{j \neq i} D_j \Big) \cdot \bar{r}\Big((D_i \cap t_i) \setminus \bigcup_{j \neq i} D_j \Big). \tag{1}$$

- **Shared Responsibility (SR$_{i \to j}$ or SR$_{i \leftarrow j}$)**: Risk averaged for regions where D_i overlaps with D_j. Direction is assigned based on the property parcel containing the overlapping region under consideration:

$$\mathrm{SR}_{i \leftarrow j} = Area\big(D_i \cap D_j \cap t_i \big) \cdot \bar{r}\big(D_i \cap D_j \cap t_i \big), \tag{2}$$

$$\mathrm{SR}_{i \to j} = Area\Big(D_i \cap D_j \cap t_j \Big) \cdot \bar{r}\big(D_i \cap D_j \cap t_j \big). \tag{3}$$

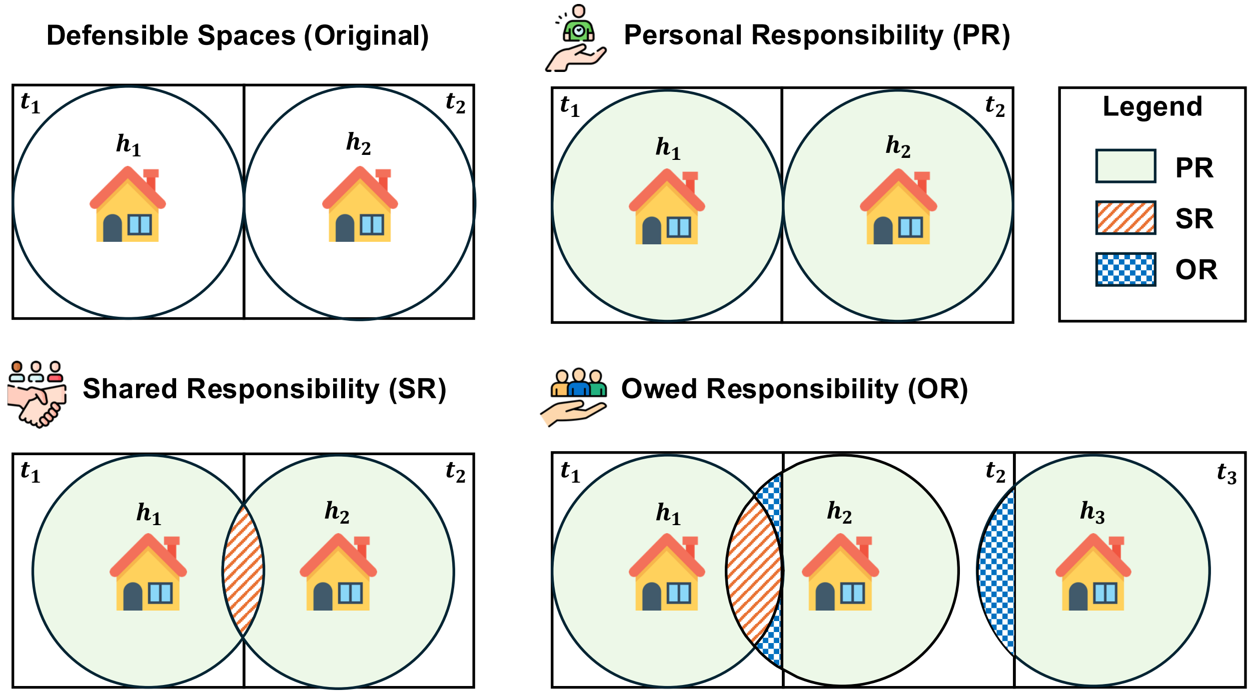

Figure 2: Diagrams of the original defensible space definition for two houses (h_1, h_2) and their respective parcels (t_1, t_2) followed by examples highlighting the three spatial responsibility metrics. Personal responsibility (PR) of h_1 corresponds to the area within t_1 and not overlapping with t_2. Shared responsibility (SR) of h_1 is the intersecting region of defensible spaces belonging to adjacent neighbors. Owed responsibility (OR) is the area when one's defensible space (e.g., h_3) overlaps with a neighbor's parcel (e.g., t_2), but not with their defensible space (h_2's defensible space).

For a given homeowner (h_i), the total shared responsibility (SR_i) is the sum of the risk averaged over all the regions where the defensible space buffers of neighboring properties overlap with D_i:

$$\mathrm{SR}_i = \sum_{j \neq i} Area\left(D_i \cap D_j \cap t_i \right) \cdot \bar{r}\left(D_i \cap D_j \cap t_i\right). \tag{4}$$

- **Owed Responsibility ($\mathbf{OR}_{i \to j}$ or $\mathbf{OR}_{i \leftarrow j}$):** Risk averaged for regions where D_i overlaps with t_j but *not* with D_j. Direction is assigned based on who is responsible for owing mitigation.

$$\mathrm{OR}_{i \to j} = Area\left(D_i \cap t_j \setminus D_j \right) \cdot \bar{r}\left(D_i \cap t_j \setminus D_j\right), \tag{5}$$

$$\mathrm{OR}_{i \leftarrow j} = Area\left(D_j \cap t_i \setminus D_i \right) \cdot \bar{r}\left(D_j \cap t_i \setminus D_i\right). \tag{6}$$

For a given homeowner (h_i), the total owed responsibility (OR_i) is the sum of the risk averaged over all the regions where the defensible space of neighboring properties overlap with only t_i and not D_i.

$$\mathrm{OR}_i = \sum_{j \neq i} Area\Big(\left(D_i \cap t_j \right) \setminus D_j \Big) \cdot \bar{r}\Big(\left(D_i \cap t_j \right) \setminus D_j \Big). \tag{7}$$

Since the spatial responsibility metrics are calculated as a product of the risk (ROS in ft/min) and area (ft^2), the responsibility is measured as an integrated metric in ft^3/min. This metric can be interpreted as the amount of risk based on fire spread potential generated for a given area per unit of time.

2.3. Spatial responsibility networks

In the WUI, the spatial distribution of structures (including site location and SSD) is an important factor in determining building survivability to wildfires [24, 51]. Adding to the complexity is the spatial heterogeneity of parcel configurations, fuel loads, and landscape exposure, which all contribute to wildfire risk. As a result, some properties may disproportionately benefit from the mitigation actions of other neighbors or, conversely, bear greater responsibility for community-wide protection. To model this interdependent risk between neighboring properties, we construct spatial responsibility networks with nodes characterized by PR (Eq. 1) and links weighted by SR (Eqs. 2 and 4) or OR (Eqs. 5 and 6). The direction of the links are determined by parcel ownership. Hence, at each node, a link exists if wildfire risk is present in the area of interest. For either SR or OR networks, nodes can possess multiple links (degree > 1) if there are multiple instances of SR or OR. In general, spatial responsibility networks may not be fully connected. Multiple sub-networks (i.e., connected components) may exist, since network topology is structured based on the neighborhood layout, spatial distribution of structures, and the defensible space buffer distance considered. We model the spatial responsibility networks using the *NetworkX* Python library.

2.4. Simulating risk mitigation using network link removal

Complex systems like socio-technical and socio-ecological systems depend on their topological connectivity to remain functional [52]. Strategic removal or deactivation of specific network nodes or links can fragment the network structure and disrupt the system, leading to potential cascading effects and catastrophic failure [53, 54]. From a planning and risk management standpoint, simulating this dismantling process is useful to identify network vulnerabilities and assess network robustness and resilience [55–57]. Similarly, network link removal algorithms have been applied in wildfire-related studies, such as the optimal placement of fire breaks [58] and fuel breaks [59] as well as the assessment of building survivability from wildfire spread [60]. Inspired by network dismantling and strategic removal techniques, we adopt this approach in our study where each link in the SR or OR network is considered as a potential pathway of wildfire risk between neighboring parcels. Removing a link therefore represents claiming responsibility and mitigating wildfire risk on one's property, such as clearing fuels and maintaining defensible space.

To simulate wildfire risk mitigation, we design three strategies for network link removal: random, localized, targeted. These strategies also reflect real-world decision-making by homeowners in WUI neighborhoods. The *random* strategy can represent uncoordinated mitigation, where homeowners act independently and fuel reduction occurs in a non-systematic, random manner. The *localized* strategy can capture clustered or block-level mitigation, where one homeowner's initial compliance prompts their neighbors to follow, reflecting coordination between close neighbors, shared contractor use, or other logistical constraints that can bias mitigation work in neighboring properties. Lastly, the *targeted* strategy reflects risk-informed planning, where mitigation is prioritized based on links with the highest SR or OR values. In our simulation, we remove links in fractional increments (e.g., 10% per timestep) until the network is fully dismantled. When links are removed, we assume that risk mitigation occurs fully and successfully for the given area. During this process, we record how each strategy reduces responsibility for each sub-network and for the entire neighborhood (i.e., total SR or OR for all sub-networks).

3. Results

3.1. Maps of spatial responsibility metrics

We used FlamMap (See Fig. 1) to simulate fire spread and computed ROS [ft/min] as a proxy for wildfire risk. We then computed average SR, PR, and OR in terms of $[ft^3/min]$ for each homeowner as shown in Fig. 3. We also calculated total responsibility as the sum of the three responsibility metrics in Fig. 3A. We mapped all metrics with respect to each house's defensible space buffer. Higher values correspond to greater levels of responsibility across all metrics. Panel A's histogram displays total responsibility and reveals a clustered pattern of higher values, a trend supported by its right-skewed data distribution indicating a peak in the 150-200 ft^3/min range. SR in Panel B also shows distinct, localized clusters of higher values with its data distribution peaking below 50 ft^3/min. Conversely, PR in Panel C appears more spatially dispersed, as its data distribution reflects a broader range across the different values. Notably, OR in Panel D is sparse and highly localized to only a few isolated units. The OR data distribution is heavily concentrated at or near zero.

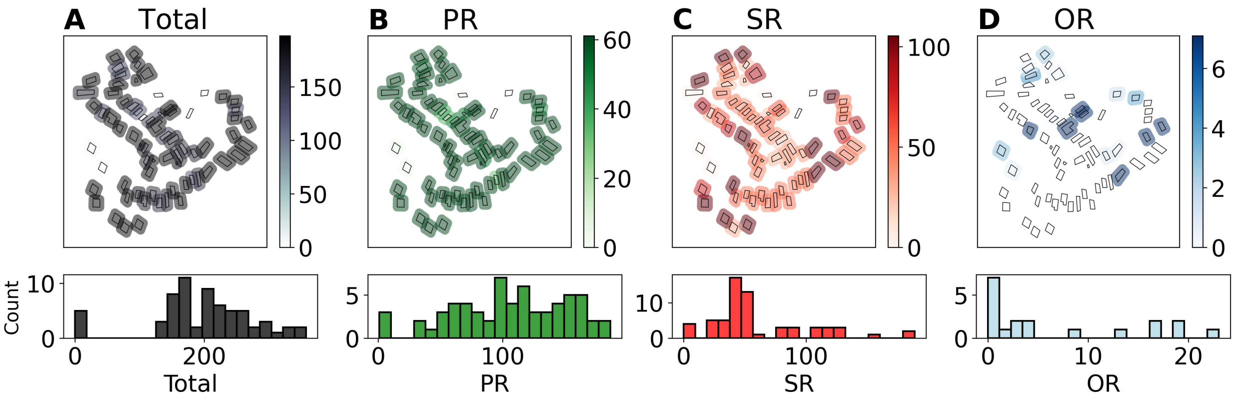

Figure 3: Spatial responsibility maps for each defensible space buffer [ft^3/min] and their data distributions. (**A**): Sum of all responsibility measures (SR, PR, OR), (**B**): Average PR, (**C**): Average SR, (**D**): Average OR

Table 1
Characteristics of SR sub-networks and their averaged value.

#	Set of Sub-network Nodes	# links	# Nodes	Average SR (ft^3/min)
1	{4, 8–10, 12–14, 19, 20, 22, 27, 29, 30, 32, 33, 35–37, 40, 48, 53, 55, 56, 60–63}	58	27	86.94
2	{16, 17, 26, 28, 31, 34, 38, 39, 44, 45, 50, 57, 59}	24	13	105.93
3	{3, 11, 15, 49, 52, 54}	10	6	114.25
4	{24, 25, 43, 58, 64}	8	5	121.69
5	{18, 42, 46, 47}	6	4	125.48
6	{0–2}	4	3	143.17
7	{5, 6}	2	2	191.08

3.2. Spatial responsibility networks

We model the spatial responsibility metrics as directed networks to show *who* is responsible and for *how much* of the risk. In comparison with the spatial responsibility maps in Fig. 3, the networks provide a more comprehensive “systems view” of the interconnected risk shared and owed within the neighborhood. In this section, we present the SR and OR networks, and we examine key insights from network topology and their responsibility values.

We first build a directed network with nodes characterized by PR and links weighted by SR as shown in Fig. 4. We visualize the network's topology in Fig. 4A, where the nodes are located at the centroid of each building in the neighborhood. The color legends illustrate the magnitude of PR (nodes) and SR (links) in ft^3/min. SR's direction is oriented with respect to the property parcel on which the overlapping area of responsibility is being considered. To clarify the visualization, we highlight Owner 12 (see focus area box in Panel A) who had the highest degree value (i.e., most number of incoming and outgoing links) and demonstrate their spatial distribution of PR and SR with neighboring properties. In Fig. 4B, we see that Owner 12's defensible space buffer overlaps with those of neighbors 27, 29, 40, and 56. To emphasize the interconnectedness in the SR network, we illustrate the connections in a circular layout in Fig. 4C. The SR network tends to be composed of sub-networks (i.e., connected components), as listed in Table 1. Interestingly, the sub-network size was inversely proportional to average SR. The largest sub-network consists of 27 nodes and 58 directed links, exhibiting an average SR value of 86.94 ft^3/min. In contrast, smaller sub-networks, such as those comprising only two or three nodes, tend to show higher average SR values, suggesting more intense localized responsibilities. Notably, the highest average SR (191.08 ft^3/min) occurs in the smallest cluster, which includes only two nodes (5 and 6). This pattern suggests that isolated or tightly coupled properties may face steeper mutual risk, potentially due to limited buffering or shared exposure.

We then construct the OR network with nodes characterized by PR and directed links weighted by OR, as depicted in Fig. 5. We display the network's topology in Fig. 5A, where nodes are positioned at the centroid of each building.

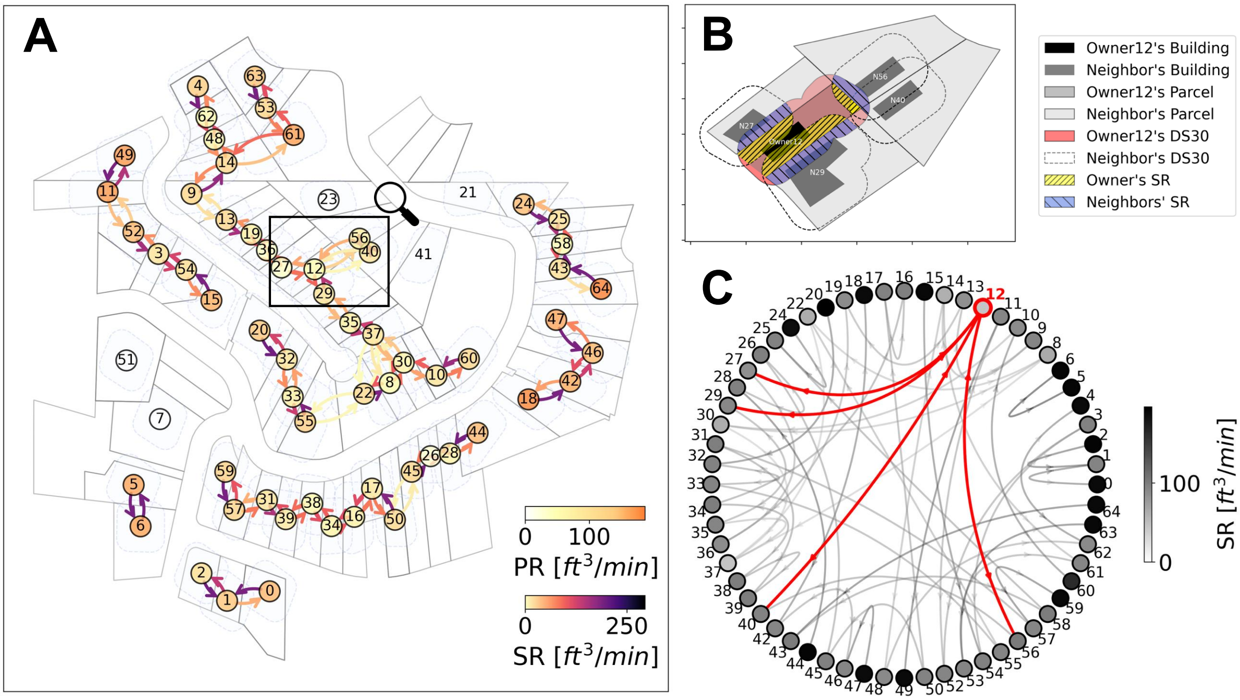

Figure 4: SR network with nodes characterized by average PR and directed links by average SR. **A)** Network's topology showing nodes located at building centroids and links weighted by SR values in ft^3/min. The link's direction is oriented towards the homeowner whose property parcel occupies the SR. A focus area box is centered on Owner 12 (most number of incoming and outgoing links). **B)** Detailed spatial distribution view of Owner 12's parcel, building, and overlapping areas displaying SR overlaps with neighbors. Owner 12's defensible space buffer overlaps with those of neighbors 27, 29, 40, and 56. **C)** Circular layout emphasizing the interconnected SR relationships, with connections involving Owner 12 highlighted in red.

OR's direction signifies the flow of overlapping responsibility from one neighbor's property to another. As an example, we highlight Owner 47 (see focus area box in Panel A), who demonstrates high OR values. In Fig. 5B, we observe that Owner 47's defensible space does not directly overlap with neighbor 64's defensible space but they share OR areas overlapping with each other's parcels. Hence, Owner 47 "owes" Neighbor 64 their OR area (blue-striped color) and Neighbor 64 "owes" Neighbor 64 their OR area (yellow-striped area). We emphasize the OR links in a circular layout in Fig. 5C, where the directed links connecting Owner 47 and Owner 64 are highlighted in red.

The OR network is characterized by several distinct sub-networks or isolated link(s), as detailed in Table 2. In contrast to SR, OR sub-networks exhibit a more fragmented and diffuse risk structure. The largest OR sub-network (sub-network #6) comprises eight nodes and seven directed links with an average OR value of 7.59 ft^3/min. Certain links exhibit relatively high average OR, such as nodes 15 and 20 as well as 18 and 40.

3.3. Comparison of mitigation scenarios

We implement network link removal based on incremental link removal to simulate risk mitigation via three strategies (*random*, *localized*, *targeted*). We iteratively remove 10% of links from the network and record the total SR and OR summed for all sub-networks. Fig. 6A and B show the network link removal results for the SR and OR networks, respectively. The points plotted in Fig. 6 represent each sub-network's average SR and OR value for the corresponding fraction of removed links. We also record the total SR and OR as well as the number of emerging sub-networks in the inset plots following incremental link removal.

Across all three strategies, the total SR for all sub-networks decreases monotonically as more links were removed. The *targeted* strategy is found to be the most effective strategy in reducing total SR, reaching near-zero values the fastest (around 70% of links removed). The *random* strategy is also relatively effective and follows a similar decreasing

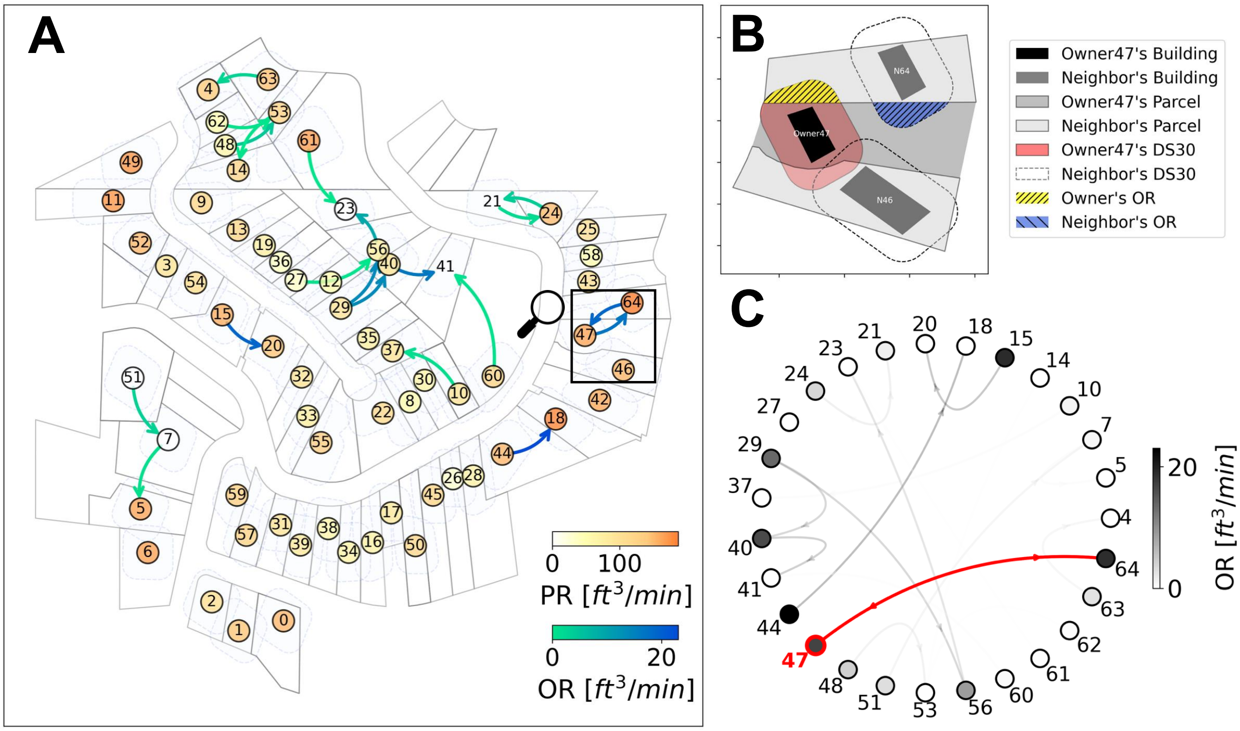

Figure 5: OR network with nodes characterized by average PR and directed links by average OR. A) Network's topology and OR links, where nodes are located at building centroids and the responsibility values are measured in ft^3/min. The link's direction denotes which owner ''owes" whom based on the parcel on which the OR overlap occurs. A focus area box is centered on Houses 47 and 64 given the high OR values in their directed links. **B)** Detailed view of Owner 12's parcel, building, and OR overlaps with neighbors. Owner 47's defensible space overlaps with those of neighbor 64. **C)** Circular layout emphasizing the interconnected OR relationships, with connections involving Owner 47 highlighted in red.

Table 2
Characteristics of OR sub-networks and their averaged value.

#	Set of Sub-network Nodes	# links	# Nodes	Average OR (ft^3/min)
1	{10, 37}	1	2	0.95
2	{5, 7, 51}	2	3	1.86
3	{14, 48, 53, 62}	3	4	1.57
4	{4, 63}	1	2	2.53
5	{21, 24}	2	2	2.58
6	{23, 27, 29, 40, 41, 56, 60, 61}	7	8	7.59
7	{47, 64}	2	2	17.92
8	{15, 20}	1	2	19.16
9	{18, 44}	1	2	23.04

trend to the *targeted* strategy, but requires removing more links to reach near-zero SR values. The *localized* strategy is the least effective, as total SR decreases linearly. The inset plots show how network link removal creates more sub-networks. In particular, the *random* and *targeted* strategies increases sub-networks peaking at 75% and 55% links removed, respectively, before reducing to zero. The *localized* strategy generates a slight but variable increase in sub-networks, but never manages to remove all sub-networks. The *localized* strategy is, therefore, sub-optimal and unable to fully mitigate all SR in the sub-networks. For the OR network, the *random* and *localized* strategies decline in a staggered manner. In contrast, the *targeted* strategy is able to reduce total OR much more rapidly, reducing to near-zero OR at around 50% link removed. This trend is expected since the OR network consists of smaller sub-networks and isolated links with high OR. The number of sub-networks decreases steadily for the *random* and *targeted* strategies. For the *localized* strategy, this decrease is much more subtle.

To evaluate the robustness of the mitigation strategies, we repeat the network link removal simulation for ten iterations and averaged the outcomes in Fig. 7. For the SR network in Fig. 7A, the *targeted* strategy is found to be the most effective, reducing total SR most quickly. The *random* and *localized* strategies perform similarly and reduce total SR in a linear manner. The only difference occurs after 80% link removal, where the localized strategy fails to completely dismantle the network. For the OR network in Fig. 7B, the *targeted* strategy is also the most effective and reduces total OR at an exponential rate, showing a substantial improvement over the other strategies. In essence, the targeted removal of links quickly fragments the OR network into small, low-risk components after removing only a small fraction of key links in the OR network. The *random* strategy decreases linearly with some variance. Similarly, the *localized* strategies decreases linearly, but at a slower rate and exhibits greater variance. These two trends suggest that randomization (random selection for the *random* strategy and the random initialization for the *localized* strategy) are important for reducing total OR.

4. Discussion

This study proposes novel spatial metrics to map and quantify the homeowner's responsibility to mitigate wildfire risk in the WUI. Spatial responsibility can foster a greater sense of accountability and collective action, encouraging homeowners to view defensible space as part of a coordinated neighborhood effort rather than an isolated and individual task. By examining defensible spaces as buffers extending beyond property boundaries, the metrics are used to measure

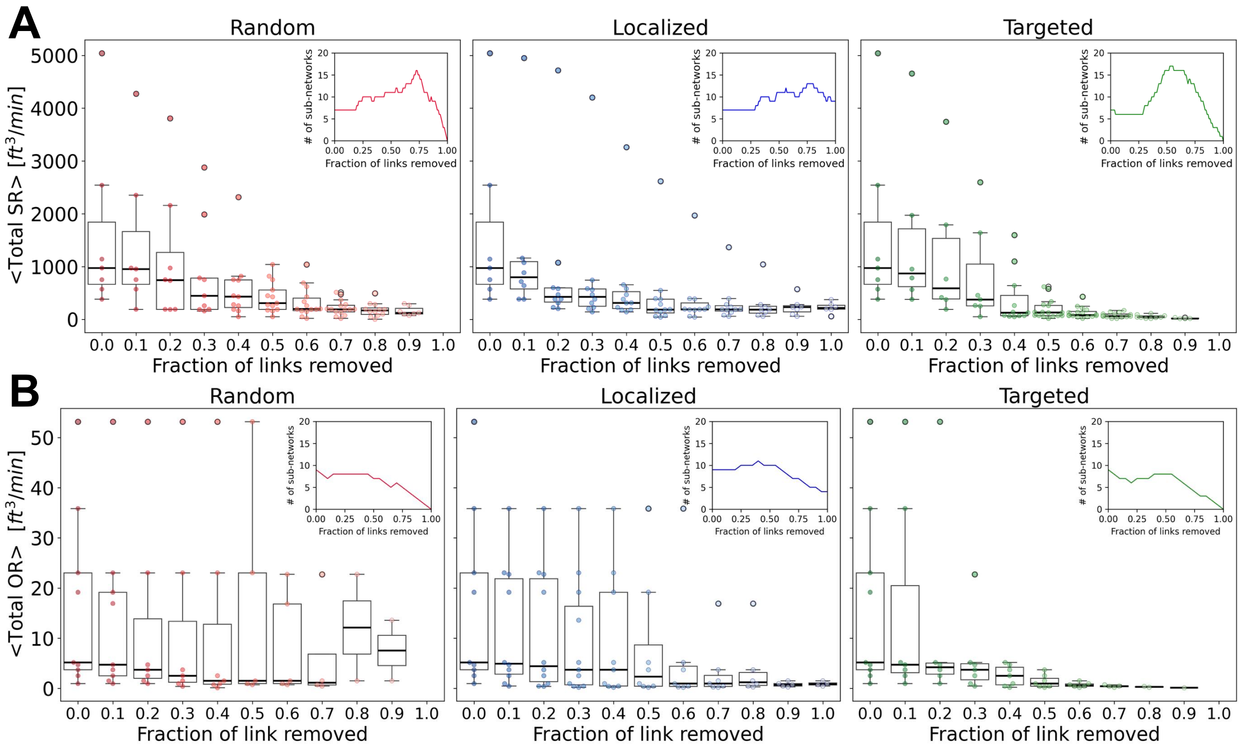

Figure 6: Impact of network link removal on SR and OR networks using three mitigation strategies (random, localized, targeted). (A) Total SR and (B) Total OR are shown as a function of the fraction of links removed in their respective network, where each point represents a sub-network and its total SR (or OR) value. The box plots show the data distribution for each fraction of links removed. The point with the highest value corresponds to the sub-network with the highest cumulative responsibility (hence, highest total risk). Inset plots are provided for each mitigation strategy, displaying the number of sub-networks for each fraction of links removed.

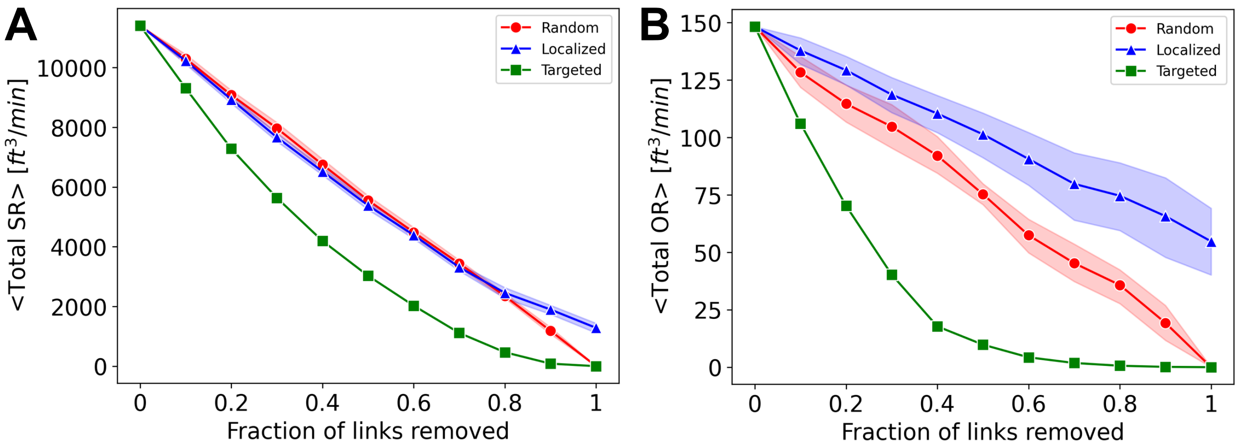

Figure 7: Comparison of network link removal strategies on SR and OR networks over ten iterations. (A) Link removal on SR network shows the targeted strategy reduces most rapidly while random and localized strategies tend to decrease linearly. (B) Link removal on OR network shows the targeted strategy reduces most rapidly especially until 40% of links removed, while the random strategy decreases linearly and the localized strategy decreases at a slower pace with greater variance as more links are removed.

and map spatial spillover of one's responsibility to mitigate risk. Subsequently, the PR, SR, and OR metrics can be used to identify *who* is responsible and for *how much* of the risk, moving beyond traditional parcel-centric analysis [42] that often overlook multi-parcel interdependencies such as risk externalities and spatial spillovers [13, 15]. We further advance this approach by connecting the metrics into directed networks of spatial responsibility. The networks represent a significant paradigm shift in wildfire risk management by re-framing risk as responsibility, addressing wildfire risk via multi-parcel analysis, and providing a networked "systems view" of each homeowner's role in the neighborhood. For implementation, we apply the metrics and build SR and OR networks. The study's results demonstrate how the metrics and networks can be used to visualize critical vulnerabilities, identify hotspots or clusters of at-risk neighbors, and delineate sub-networks for potential collaboration. The simulated mitigation strategies via network link removal offer practical scenarios to support resource allocation, defensible space inspections, and informed decision-making for policymakers and individual homeowners.

4.1. Spatial responsibility maps and networks can innovate wildfire risk management

Mapping wildfire risk at the parcel-level is needed for risk mitigation, land use planning, insurance, and policy-making. Surveys in the literature indicate that a lack of parcel-scale risk information hinders homeowners from deciding to mitigate [61], especially personalized information for those in areas of higher wildfire risk [62]. Even the spatially-explicit maps of PR, SR, and OR (see Fig. 2) provide a more nuanced understanding of homeowner responsibility for wildfire risk mitigation. In the neighborhood layout used in our study, PR values tended to be higher on average than SR and OR (PR_{avg}: 105.39 ft^3/min, SR_{avg}: 61.07 ft^3/min, OR_{avg}: 7.09 ft^3/min). This is likely because PR regions cover more area relative to SR and OR. This information can also complement existing parcel-scale wildfire risk studies [17, 42].

While PR, SR, and OR maps in Fig. 2 are derived from multi-parcel information, the homeowner's role is still unclear without integrating directionality. Connecting spatial responsibility metrics into spatial networks thus provides nuanced information on homeowner roles and risk on their property. The fragmentation into multiple sub-networks highlights critical structural features of responsibility distribution within communities. Notably, we observe that smaller sub-networks tend to exhibit significantly higher average SR values compared to larger, more connected networks. This pattern suggests that nodes in isolated or poorly connected clusters can bear a disproportionate amount of responsibility. Some of these connections recorded high SR and occur on the links of the network (e.g., Houses 5 and 6). If fire conditions push fire spread from the southwest, these links may be most vulnerable to ignition and fire propagation in the neighborhood. In contrast, larger sub-networks (e.g., sub-network 1 in Table 1) tend to distribute SR more across nodes, lowering the average SR and burden on individual parcels. However, this comes at the cost of greater complexity due to more connected neighbors. Another result was that larger sub-networks possess higher cumulative SR. Since even non-compliance from one property can expose the connected sub-network (and potentially the entire neighborhood) to damages from fire spread, more coordination is needed to motivate mitigation in these larger groups. Since OR links occur more sparsely, OR areas can be overlooked as they may not directly expose neighboring structures unless identified appropriately. Further, while OR values are lower in magnitude in comparison to PR and SR, specific links (e.g., Houses 18 and 44) exhibit high average OR and hotspots (e.g., OR sub-network 6) possess high cumulative OR, which may present critical vulnerabilities. Stemming from these findings, the metrics and networks can help empower homeowner decision-making as well as inform local governments and community-scale programs such as Firewise and Fire Safe councils to facilitate risk mitigation measures.

4.2. Network link removal simulations help proactive wildfire risk mitigation

Traditional funding mechanisms for wildfire mitigation typically do not consider spatial variability of risk or spatial spillover effects [43]. The network link removal simulation thus offers a new lens to integrate spatial responsibility networks and understand how prioritizing specific components can influence the efficiency of wildfire risk mitigation. Our selection of mitigation strategies (random, localized, targeted) encompasses a reasonable range of theoretical scenarios for community-level planning. These strategies are important to consider because it is up to the individual homeowner to apply for funded grant programs, which limits participation based on awareness of funding existence, application requirements, and upfront costs [43]. In our study, the random strategy acted as the baseline scenario, which seldom occurs in practice since homeowners in the WUI tend to be collectively aware and informed about wildfire risk. The localized strategy reflects potential neighbor interactions (e.g., mitigation grant applications via word-of-mouth) or the result of grouping nearby houses. Intuitively, the targeted scenario is ideal, yet is difficult to implement without risk information at the homeowner level. Through our study, we present that the targeted strategy led to the most significant rate of decrease in SR and OR. This finding suggests that wildfire risk is heterogeneous and not evenly distributed, such that mitigating specific high-SR and high-OR properties can lead to substantial reductions in wildfire risk across the entire neighborhood. By identifying key links in the SR and OR networks, these results can help inform resource allocation and mitigation priorities to reduce risk while conserving limited resources. The network modeling and techniques can also be used in a practical framework for guiding wildfire mitigation planning by integrating additional criteria such as socioeconomic data, fire history, and other parcel-scale information.

4.3. Leveraging spatial responsibility networks to build community resilience

Spatial responsibility networks can help foster collaborations between neighbors and build social cohesion within the WUI community. Developing social ties is important to establish adaptive and transformative resilience against wildfire risk [48]. Since each sub-network represents a group of houses with interconnected responsibilities, the corresponding homeowners can be gathered for community-based outreach related to wildfire management, communication, and collaboration. The networks and their components thus offer a starting point to bring at-risk homeowners together and serve as a planning tool to facilitate community engagement and foster long-term resilience. The metrics and networks also help enhance risk communication. By visualizing the interconnectedness of risk, spatial responsibility maps and networks can help homeowners to picture risk and forge potential collaborations for mitigation. This also facilitates neighborhood cooperation where communities provide grants for collaborative mitigation efforts. The spatial information can also be integrated into geospatial software for post-processing and visualization in dashboards and basemaps for increased interactive engagement.

The effectiveness of wildfire risk mitigation in the WUI hinges not only on understanding physical risk and fire behavior, but also on the behavioral dynamics of homeowners. For instance, game-theoretic models can capture the tensions between self-interest and collective benefit in wildfire mitigation [29, 30], identifying potential free-riding behavior or tipping points at which cooperation becomes more likely. Similarly, insights from system dynamics and epidemiological modeling can be adapted to explore how risk awareness, treatment adoption, and information spread across networks over time [63]. These models can reveal critical thresholds (behavioral or structural) at which individual action triggers cascading risk reduction across a neighborhood. This prospect can opens new avenues for designing incentive structures, educational campaigns, and policy interventions that align individual behavior with collective outcomes.

4.4. Limitations and future directions

One limitation is the selection of our study's neighborhood layout. Our study area consisted of 70 houses, which is similar in magnitude to recent theoretical studies [64]. However, neighborhood layouts can vary significantly. For instance, neighborhoods in the intermix may be more sparsely distributed with property parcels that are irregularly shaped. Moreover, neighborhoods closer to the urban center may need to deal with publicly owned lands with larger property parcels that may bias the calculation of spatial responsibility metrics. Considering the complexity of neighborhood layouts, we need to ensure that WUI policies are not static and form-based (i.e., "one-size fits all"), but are process-based to address the dynamic nature of wildfire risk [49]. While our study considered a fixed 30-ft defensible space buffer around the buildings based on Public Law Code: CA PRC 4291, it would be interesting to consider multiple defensible space zones according to the density of housing units and complex layouts in real neighborhoods. For instance, the home ignition zone (5-ft buffer) is crucial for fire protection and building survivability [15]. In sparsely distributed neighborhoods under high wildfire risk like in the intermix, larger buffer distances may also be considered. In such cases the OR metric may be preferred since any flammable hazards in these areas may be difficult to identify and excluded from inspections.

Our study also opens new opportunities to assess the effectiveness of defensible spaces against real wildfires in the WUI. For instance, Norton [44] compared critical zones (mutual, excluded, isolated) of interconnected risk (i.e., flame length) in WUI neighborhoods affected by the 2018 Woolsey Fire and discovered that 98% of the damaged buildings did not comply with adequate defensible space standards (i.e., high risk features present in critical zones based on potential flame length greater than 11 ft) and the fact that these vulnerabilities may be significantly underestimated because current defensible space inspections rely on average weather conditions instead of red flag conditions similar to actual wildfire events. Instead of relying on "one-size-fits-all" solutions, there is a pressing need to use property assessment models that can better define *adequate* defensible spaces based on the variable conditions (including climate, terrain, vegetation, and built structures) for each property and its neighborhood. As mentioned above, future research on wildfire risk mitigation should not limit current defensible space policies as static, form-based definitions but should consider the dynamic nature of wildfire risk. This means ensuring that these policies are process-based and supported by science, such that they can be robust to different risk conditions. This consideration is critical because, even if all homeowners comply with *current* defensible space criteria, it does not guarantee that the neighborhood would be able to withstand more severe wildfires in the future. To improve chances of structure survivability, maximize firefighter safety, and build more fire-resilient communities, defensible spaces need to be maintained considering future risks and potential fire weather conditions. An advantage of our proposed spatial responsibility metrics is that they are agnostic to neighborhood layouts and measures of risk. To advance this study, the spatial responsibility metrics and networks can be compared using risk metrics under different fire weather conditions and scenarios. In addition, these metrics can be compared with building damage data derived from very high resolution remote sensing data [65, 66] or curated databases such as the Damage Inspection data from CALFIRE.

Another limitation is our characterization of wildfire risk. We used FlamMap to compute the potential fire behavior (ROS) by reclassifying structures as the SB4 (high-load blowdown) fuel model [50]. While this assumption underestimates the complexity of fire dynamics with structural fuels, we consider this to reflect the worst-case scenario in the fire spread simulation. More sophisticated measures of risk may consider using WUI fire spread models and ember dynamics to better model fire propagation [24, 67–69]. Also, our study uses potential fire behavior (ROS) as a proxy, but different risk metrics can be used to compute the responsibility metrics. When selecting risk metrics, however, one should also consider the resolution and complexity of the data. Although wildfire risk maps are widely available in the U.S. [41], higher spatial resolution data (less than 30 m) is needed to resolve features in defensible space buffers such as urban vegetation and fuels in the WUI [22]. Recent studies also suggest that higher spatial resolution fuel data (e.g., 5 to 10 m resolution) helps identify critical landscape features such as roads and vegetation gaps that slow or block fire spread [70] and resolve fuel heterogeneity. We also do not consider other structures or flammable materials in the simulation such as fences, decks, and accessory dwelling units [15]. Future works may consider mitigation actions such as retrofitting and home hardening in their risk estimates [71]. These additions would help improve the realism and predictive power of the spatial responsibility networks.

One other limitation is our assumption regarding the homeowner's decision to mitigate. While we assume that homeowners will completely mitigate all risk in the network link removal simulations, homeowner behavior can vary significantly based on different social factors, risk perception, and mitigation capability [31, 35, 39]. Our study assumed one ideal case and does not account for the social, legal, or physical feasibility of collaboration between neighbors. For example, a homeowner's willingness to mitigate can be attributed various barriers (financial, knowledge, legal) that hinder one's ability to modify certain parts of the landscape [71]. Future research can combine our spatial responsibility metrics with these factors to enhance our understanding of human behavior and improve the feasibility of wildfire risk mitigation [35, 39]. Aside from homeowner behavior, we also do not consider the different types of residents (e.g., renters) and the type of housing unit. These factors can further impact the homeowner's motivation to mitigate and collaborate in risk management [2]. By mapping the shared and owed regions as well as computing SR and OR networks, future research may find potential inequities in the spatial distribution of wildfire risk in a neighborhood. These observations can also be significant to consider when allocating funds and resources for defensible space inspections and maintenance.

5. Conclusion

This study presents a novel framework for quantifying and visualizing shared, personal, and owed responsibility for wildfire risk mitigation in WUI neighborhoods at the homeowner scale. By extending defensible space buffers beyond parcel boundaries and modeling spatial relationships as directed networks, we demonstrate how wildfire risk is collectively produced and differentially shared among neighbors. Our study presents spatial responsibility maps and networks, which can be used to identify *who* is responsible and for *how much* risk. Our study compared various mitigation strategies via network link removal and found that targeted interventions (guided in order of highest to lowest SR and OR values) can significantly reduce fire spread potential with minimal effort, offering a valuable strategy for wildfire risk mitigation and management. The identification of hotspots and vulnerable sub-networks can help prepare and plan for more equitable and efficient allocation of mitigation resources. As wildfire events become more frequent and severe, this work lays the groundwork for spatial responsibility assessments that move beyond awareness and toward actionable, community-scale interventions. Future research can build upon this framework to incorporate temporal dynamics, social behavior models, and policy testing, ultimately supporting fire-resilient planning and more equitable risk management in the WUI.

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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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CRediT authorship contribution statement

Minho Kim: Conceptualization, Methodology, Software, Visualization, Formal Analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing. **Harrison Raine:** Conceptualization, Data Curation, Writing – review & editing. **John Radke:** Conceptualization, Writing – review & editing, Supervision. **Marta C. González:** Conceptualization, Methodology, Writing – review & editing, Formal Analysis, Supervision, Project administration, Funding acquisition.

References

[1] John Radke. Modeling urban/wildland interface fire hazards within a geographic information system. *Geographic Information Sciences*, 1(1): 9–21, 1995.

[2] Gwenlyn Busby and Heidi J Albers. Wildfire risk management on a landscape with public and private ownership: who pays for protection? *Environmental Management*, 45(2):296–310, 2010.

[3] Volker C Radeloff, David P Helmers, H Anu Kramer, Miranda H Mockrin, Patricia M Alexandre, Avi Bar-Massada, Van Butsic, Todd J Hawbaker, Sebastián Martinuzzi, Alexandra D Syphard, et al. Rapid growth of the us wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, 115(13):3314–3319, 2018.

[4] Volker C Radeloff, Miranda H Mockrin, David Helmers, Amanda Carlson, Todd J Hawbaker, Sebastian Martinuzzi, Franz Schug, Patricia M Alexandre, H Anu Kramer, and Anna M Pidgeon. Rising wildfire risk to houses in the united states, especially in grasslands and shrublands. *Science*, 382(6671):702–707, 2023.

[5] Franz Schug, Avi Bar-Massada, Amanda R Carlson, Heather Cox, Todd J Hawbaker, David Helmers, Patrick Hostert, Dominik Kaim, Neda K Kasraee, Sebastián Martinuzzi, et al. The global wildland–urban interface. *Nature*, 621(7977):94–99, 2023.

[6] Bin Chen, Shengbiao Wu, Yufang Jin, Yimeng Song, Chao Wu, Sergey Venevsky, Bing Xu, Chris Webster, and Peng Gong. Wildfire risk for global wildland–urban interface areas. *Nature Sustainability*, 7(4):474–484, 2024.

[7] A Paige Fischer, Thomas A Spies, Toddi A Steelman, Cassandra Moseley, Bart R Johnson, John D Bailey, Alan A Ager, Patrick Bourgeron, Susan Charnley, Brandon M Collins, et al. Wildfire risk as a socioecological pathology. *Frontiers in Ecology and the Environment*, 14(5): 276–284, 2016.

[8] Max A Moritz, Enric Batllori, Ross A Bradstock, A Malcolm Gill, John Handmer, Paul F Hessburg, Justin Leonard, Sarah McCaffrey, Dennis C Odion, Tania Schoennagel, et al. Learning to coexist with wildfire. *Nature*, 515(7525):58–66, 2014.

[9] Maria-Luisa Chas-Amil, Emilio Nogueira-Moure, Jeffrey P Prestemon, and Julia Touza. Spatial patterns of social vulnerability in relation to wildfire risk and wildland-urban interface presence. *Landscape and urban planning*, 228:104577, 2022.

[10] David Beltrán-Marcos, Leonor Calvo, José Manuel Fernández-Guisuraga, Víctor Fernández-García, and Susana Suárez-Seoane. Wildland-urban interface typologies prone to high severity fires in spain. *Science of the Total Environment*, 894:165000, 2023.

[11] David E Calkin, Jack D Cohen, Mark A Finney, and Matthew P Thompson. How risk management can prevent future wildfire disasters in the wildland-urban interface. *Proceedings of the National Academy of Sciences*, 111(2):746–751, 2014.

[12] Timothy Ingalsbee and Urooj Raja. The rising costs of wildfire suppression and the case for ecological fire use. In *The ecological importance of mixed-severity fires*, pages 348–371. Elsevier, 2015.

[13] Jude Bayham, Jonathan K Yoder, Patricia A Champ, and David E Calkin. The economics of wildfire in the united states. *Annual Review of Resource Economics*, 14(1):379–401, 2022.

[14] Max A Moritz, Rob Hazard, Kelly Johnston, Marc Mayes, Molly Mowery, Katie Oran, Anne-Marie Parkinson, David A Schmidt, and Graham Wesolowski. Beyond a focus on fuel reduction in the wui: the need for regional wildfire mitigation to address multiple risks. *Frontiers in Forests and Global Change*, 5:848254, 2022.

[15] Alexander Maranghides, Eric D Link, Shonali Nazare, Steven Hawks, Jim McDougald, Stephen L Quarles, Daniel J Gorham, et al. *WUI Structure/parcel/community fire hazard mitigation methodology*. US Department of Commerce, National Institute of Standards and Technology, 2022.

[16] Jack D Cohen. Reducing the wildland fire threat to homes: where and how much? In *In: Gonzales-Caban, Armando; Omi, Philip N., technical coordinators. Proceedings of the Symposium on Fire Economics, Planning, and Policy: Bottom Lines; 1999 April 5-9. San Diego, CA. Gen. Tech. Rep. PSW-GTR-173. Albany, CA: US Department of Agriculture, Forest Service, Pacific Southwest Research Station. p. 189-195*, 1999.

[17] Alexandra D Syphard, Teresa J Brennan, and Jon E Keeley. The role of defensible space for residential structure protection during wildfires. *International Journal of Wildland Fire*, 23(8):1165–1175, 2014.

[18] Sandra H Penman, Owen F Price, Trent D Penman, and Ross A Bradstock. The role of defensible space on the likelihood of house impact from wildfires in forested landscapes of south eastern australia. *International journal of wildland fire*, 28(1):4–14, 2018.

[19] Kristin H Braziunas, Rupert Seidl, Werner Rammer, and Monica G Turner. Can we manage a future with more fire? effectiveness of defensible space treatment depends on housing amount and configuration. *Landscape Ecology*, 36(2):309–330, 2021.

[20] Stefania Ondei, Owen F Price, and David MJS Bowman. Garden design can reduce wildfire risk and drive more sustainable co-existence with wildfire. *npj Natural Hazards*, 1(1):18, 2024.

[21] Avi Bar Massada, Volker C Radeloff, and Susan I Stewart. Allocating fuel breaks to optimally protect structures in the wildland–urban interface. *International Journal of Wildland Fire*, 20(1):59–68, 2011.

[22] Francisco J Escobedo, Kamini Yadav, Onofrio Cappelluti, and Nels Johnson. Exploring urban vegetation type and defensible space's role in building loss during wildfire-driven events in california. *Landscape and Urban Planning*, 262:105421, 2025.

[23] Eric E Knapp, Yana S Valachovic, Stephen L Quarles, and Nels G Johnson. Housing arrangement and vegetation factors associated with single-family home survival in the 2018 camp fire, california. *Fire Ecology*, 17(1):25, 2021.

[24] Maryam Zamanialaei, Daniel San Martin, Maria Theodori, Dwi Marhaendro Jati Purnomo, Ali Tohidi, Chris Lautenberger, Yiren Qin, Arnaud Trouvé, and Michael Gollner. Fire risk to structures in california's wildland-urban interface. *Nature Communications*, 16(1):8041, 2025.

[25] Marc Castellnou, Núria Prat-Guitart, Etel Arilla, Asier Larrañaga, Edgar Nebot, Xavier Castellarnau, Jordi Vendrell, Josep Pallàs, Joan Herrera, Marc Monturiol, et al. Empowering strategic decision-making for wildfire management: avoiding the fear trap and creating a resilient landscape. *Fire ecology*, 15:1–17, 2019.

[26] Terry K Haines, Cheryl R Renner, and Margaret A Reams. A review of state and local regulation for wildfire mitigation. *The Economics of Forest Disturbances: Wildfires, Storms, and Invasive Species*, pages 273–293, 2008.

[27] Thomas J Cova. Public safety in the urban–wildland interface: should fire-prone communities have a maximum occupancy? *Natural Hazards Review*, 6(3):99–108, 2005.

[28] Bryce A Young, Matthew P Thompson, Christopher J Moran, and Carl A Seielstad. Modeling neighborhoods as fuel for wildfire: A review. *Fire Technology*, pages 1–23, 2025.

[29] Aric P Shafran. Risk externalities and the problem of wildfire risk. *Journal of urban economics*, 64(2):488–495, 2008.

[30] Travis Warziniack, Patricia Champ, James Meldrum, Hannah Brenkert-Smith, Christopher M Barth, and Lilia C Falk. Responding to risky neighbors: testing for spatial spillover effects for defensible space in a fire-prone wui community. *Environmental and Resource Economics*, 73:1023–1047, 2019.

[31] Hannah Brenkert-Smith, Patricia A Champ, and Nicholas Flores. Insights into wildfire mitigation decisions among wildland–urban interface residents. *Society and Natural Resources*, 19(8):759–768, 2006.

[32] Blythe McLennan and Michael Eburn. Exposing hidden-value trade-offs: sharing wildfire management responsibility between government and citizens. *International Journal of Wildland Fire*, 24(2):162–169, 2014.

[33] Katherine L Dickinson, Hannah Brenkert-Smith, Greg Madonia, and Nicholas E Flores. Risk interdependency, social norms, and wildfire mitigation: a choice experiment. *Natural Hazards*, 103:1327–1354, 2020.

[34] Katherine Dickinson, Hannah Brenkert-Smith, Patricia Champ, and Nicholas Flores. Catching fire? social interactions, beliefs, and wildfire risk mitigation behaviors. *Society & Natural Resources*, 28(8):807–824, 2015.
[35] Hannah Brenkert-Smith, Patricia A Champ, and Nicholas Flores. Trying not to get burned: Understanding homeowners' wildfire risk–mitigation behaviors. *Environmental Management*, 50:1139–1151, 2012.
[36] David Butry and Geoffrey Donovan. Protect thy neighbor: investigating the spatial externalities of community wildfire hazard mitigation. *Forest Science*, 54(4):417–428, 2008.
[37] Pamela Jakes, Linda Kruger, Martha Monroe, Kristen Nelson, and Victoria Sturtevant. Improving wildfire preparedness: lessons from communities across the us. *Human Ecology Review*, pages 188–197, 2007.
[38] Sarah M McCaffrey, Melanie Stidham, Eric Toman, and Bruce Shindler. Outreach programs, peer pressure, and common sense: what motivates homeowners to mitigate wildfire risk? *Environmental Management*, 48:475–488, 2011.
[39] Ji Yun Lee, Fangjiao Ma, and Yue Li. Understanding homeowner proactive actions for managing wildfire risks. *Natural Hazards*, 114(2): 1525–1547, 2022.
[40] Mark A Finney. An overview of flammap fire modeling capabilities. In *In: Andrews, Patricia L.; Butler, Bret W., comps. 2006. Fuels Management-How to Measure Success: Conference Proceedings. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 213-220*, volume 41, 2006.
[41] Joe H Scott, Julie W Gilbertson-Day, Christopher Moran, Gregory K Dillon, Karen C Short, and Kevin C Vogler. Wildfire risk to communities: Spatial datasets of landscape-wide wildfire risk components for the united states. 2020.
[42] James R Meldrum, Christopher M Barth, Julia B Goolsby, Schelly K Olson, Adam C Gosey, James White, Hannah Brenkert-Smith, Patricia A Champ, and Jamie Gomez. Parcel-level risk affects wildfire outcomes: insights from pre-fire rapid assessment data for homes destroyed in 2020 east troublesome fire. *Fire*, 5(1):24, 2022.
[43] B Amelia Pludow and Alan T Murray. Accounting for spatial spillover benefits in neighborhood wildfire risk mitigation. *Landscape and Urban Planning*, 233:104684, 2023.
[44] Peter Norton. Computing Defensibility: How High Resolution Defensible Space Modeling Can Identify Wind-Driven Wildfire Risks in the Wildland-Urban Interface. Masters thesis, University of California, Berkeley, 2020.
[45] Ulrich Beck. World risk society as cosmopolitan society? ecological questions in a framework of manufactured uncertainties. *Theory, culture & society*, 13(4):1–32, 1996.
[46] Anthony Giddens. Risk and responsibility. *Mod. L. Rev.*, 62:1, 1999.
[47] Blythe J McLennan and John Handmer. Reframing responsibility-sharing for bushfire risk management in australia after black saturday. *Environmental Hazards*, 11(1):1–15, 2012.
[48] David B McWethy, Tania Schoennagel, Philip E Higuera, Meg Krawchuk, Brian J Harvey, Elizabeth C Metcalf, Courtney Schultz, Carol Miller, Alexander L Metcalf, Brian Buma, et al. Rethinking resilience to wildfire. *Nature Sustainability*, 2(9):797–804, 2019.
[49] Anna Serra-Llobet, John Radke, G Mathias Kondolf, Larry Gurrola, J David Rogers, Sarah Lindbergh, and Johnny Douvinet. Risk as a process: a history informed hazard planning approach applied to the 2018 post-fire debris flows, montecito, california. *Frontiers in environmental science*, 11:1183324, 2023.
[50] Joe H Scott and Robert E Burgan. *Standard fire behavior fuel models: a comprehensive set for use with Rothermel's surface fire spread model*. US Department of Agriculture, Forest Service, Rocky Mountain Research Station, 2005.
[51] Patricia M Alexandre, Susan I Stewart, Miranda H Mockrin, Nicholas S Keuler, Alexandra D Syphard, Avi Bar-Massada, Murray K Clayton, and Volker C Radeloff. The relative impacts of vegetation, topography and spatial arrangement on building loss to wildfires in case studies of california and colorado. *Landscape ecology*, 31(2):415–430, 2016.
[52] Xiao-Long Ren, Niels Gleinig, Dirk Helbing, and Nino Antulov-Fantulin. Generalized network dismantling. *Proceedings of the national academy of sciences*, 116(14):6554–6559, 2019.
[53] Réka Albert, Hawoong Jeong, and Albert-László Barabási. Error and attack tolerance of complex networks. *nature*, 406(6794):378–382, 2000.
[54] Sergey V Buldyrev, Roni Parshani, Gerald Paul, H Eugene Stanley, and Shlomo Havlin. Catastrophic cascade of failures in interdependent networks. *Nature*, 464(7291):1025–1028, 2010.
[55] Aleksandar Bauranov, Steven Parks, Xuan Jiang, Jasenka Rakas, and Marta C González. Quantifying the resilience of the us domestic aviation network during the covid-19 pandemic. *Frontiers in Built Environment*, 7:642295, 2021.
[56] Nishant Yadav, Samrat Chatterjee, and Auroop R Ganguly. Resilience of urban transport network-of-networks under intense flood hazards exacerbated by targeted attacks. *Scientific reports*, 10(1):10350, 2020.
[57] Oriol Artime, Marco Grassia, Manlio De Domenico, James P Gleeson, Hernán A Makse, Giuseppe Mangioni, Matjaž Perc, and Filippo Radicchi. Robustness and resilience of complex networks. *Nature Reviews Physics*, 6(2):114–131, 2024.
[58] Marc Demange, Alessia Di Fonso, Gabriele Di Stefano, and Pierpaolo Vittorini. Network theory applied to preparedness problems in wildfire management. *Safety science*, 152:105762, 2022.
[59] Bruno A Aparício, José MC Pereira, Francisco C Santos, Chiara Bruni, and Ana CL Sá. Combining wildfire behaviour simulations and network analysis to support wildfire management: A mediterranean landscape case study. *Ecological Indicators*, 137:108726, 2022.
[60] Akshat Chulahwat, Hussam Mahmoud, Santiago Monedero, Francisco Jośe Diez Vizcaíno, Joaquin Ramirez, David Buckley, and Adrián Cardil Forradellas. Integrated graph measures reveal survival likelihood for buildings in wildfire events. *Scientific reports*, 12(1):15954, 2022.
[61] James R Meldrum, Hannah Brenkert-Smith, Patricia A Champ, Lilia Falk, Pamela Wilson, and Christopher M Barth. Wildland–urban interface residents' relationships with wildfire: variation within and across communities. *Society & Natural Resources*, 31(10):1132–1148, 2018.
[62] James R Meldrum, Hannah Brenkert-Smith, Patricia A Champ, Jamie Gomez, Hilary Byerly, Lilia Falk, and Christopher M Barth. Would you like to know more? the effect of personalized wildfire risk information and social comparisons on information-seeking behavior in the wildland–urban interface. *Natural hazards*, 106(3):2139–2161, 2021.
[63] Hussam Mahmoud. Leveraging epidemic network models towards wildfire resilience. *Nature Computational Science*, 4(4):253–256, 2024.

[64] Howard Kunreuther, Artem Demidov, Mark Pauly, Matija Turcic, and Michael Wilson. Externalities in the wildland–urban interface: Private decisions, collective action, and results from wildfire simulation models for california. *Risk analysis*, 43(5):886–895, 2023.

[65] Ritwik Gupta, Bryce Goodman, Nirav Patel, Ricky Hosfelt, Sandra Sajeev, Eric Heim, Jigar Doshi, Keane Lucas, Howie Choset, and Matthew Gaston. Creating xbd: A dataset for assessing building damage from satellite imagery. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops*, pages 10–17, 2019.

[66] Marios Galanis, Krishna Rao, Xinle Yao, Yi-Lin Tsai, Jonathan Ventura, and G Andrew Fricker. Damagemap: A post-wildfire damaged buildings classifier. *International Journal of Disaster Risk Reduction*, 65:102540, 2021.

[67] Hussam Mahmoud and Akshat Chulahwat. Unraveling the complexity of wildland urban interface fires. *Scientific Reports*, 8(1):9315, 2018.

[68] Nima Masoudvaziri, Fernando Szasdi Bardales, Oguz Kaan Keskin, Amir Sarreshtehdari, Kang Sun, and Negar Elhami-Khorasani. Streamlined wildland-urban interface fire tracing (swuift): modeling wildfire spread in communities. *Environmental Modelling & Software*, 143:105097, 2021.

[69] Dwi MJ Purnomo, Yiren Qin, Maria Theodori, Maryam Zamanialaei, Chris Lautenberger, Arnaud Trouvé, and Michael Gollner. Reconstructing modes of destruction in wildland–urban interface fires using a semi-physical level-set model. *Proceedings of the Combustion Institute*, 40 (1-4):105755, 2024.

[70] Ritu Taneja, James Hilton, Luke Wallace, Karin Reinke, and Simon Jones. Effect of fuel spatial resolution on predictive wildfire models. *International journal of wildland fire*, 30(10):776–789, 2021.

[71] Aishwarya Borate, Omar Pérez Figueroa, Douglas Houston, Christopher Ihinegbu, Ariane Jong-Levinger, Jochen E Schubert, and Brett F Sanders. Mitigation behaviors of homeowners and renters in the wildland urban interface. *International Journal of Disaster Risk Reduction*, page 105688, 2025.