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Research Paper

Archetypes of community wildfire exposure from national forests of the western US

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ABSTRACT

Risk management typologies and their resulting archetypes can structure the many social and biophysical drivers of community wildfire risk into a set number of strategies to build community resilience. Existing typologies omit key factors that determine the scale and mechanism by which exposure from large wildfires occur. These factors are particularly important for land managing agencies like the US Forest Service, which must weigh community wildfire exposure against other management priorities. We analyze community wildfire exposure from national forests by associating conditions that affect exposure in the areas where wildfires ignite to conditions where exposure likely occurs. Linking source and exposure areas defines the scale at which cross-boundary exposure from large wildfires occurs and the scale at which mitigation actions need to be planned. We find that the vast majority of wildfire exposure from national forests is concentrated among a fraction of communities that are geographically clustered in discrete pockets. Among these communities, exposure varies primarily based on development patterns and vegetation gradients and secondarily based on social and ecological management constraints. We describe five community exposure archetypes along with their associated risk mitigation strategies. Only some archetypes have conditions that support hazardous fuels programs. Others have conditions where managing community exposure through vegetation management is unlikely to suffice. These archetypes reflect the diversity of development patterns, vegetation types, associated fuels, and management constraints that exist in the western US and provide a framework to guide public investments that improve management of wildfire risk within threatened communities and on the public lands that transmit fires to them.

1. Introduction

The increase of wildfire risk in many regions around the world has prompted a wide-ranging discussion of responsible drivers, potential solutions, and how communities and land managing organizations can adapt to these changes (Smith et al., 2016). Existing wildfire risk policy has been ineffective at mitigating these trends, in large part due to overly general prescriptions that have failed to account for the diversity of social and ecological factors that shape wildfire risk. Typologies are used in natural disaster risk management to match mitigation programs to a diverse set of exposure factors (Mileti, 1999), and in the case of wildfire, the biophysical and social dimensions of risk (Steelman, 2016). A typology that combines social and biophysical aspects of wildfire exposure has the potential to improve risk governance systems by highlighting specific priorities and trade-offs among mitigation and adaptation strategies across diverse public and private landscapes (Smith et al., 2016; Spies et al., 2014).

Wildfire risk concentrates within the Wildland-Urban Interface (WUI), the area where development and infrastructure are located within or adjacent to wildland vegetation (e.g., forests, shrublands, grasslands). Combined with longer fire seasons, altered ignition patterns, and accumulation of fuels, growth of the WUI has accelerated suppression costs and wildfire-related losses (Schoennagel et al., 2017). The exact definition of the WUI varies by country and statute. In the US, the two classes of WUI most commonly described are the *intermix WUI*, where development is scattered within wildlands, and the *interface WUI,* where development abuts wildlands (USDA and USDI, 2001). Maps depicting the extent of WUI in the US now span more than two

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decades and show that growth of WUI has surpassed that of any other major land cover class (Radeloff et al., 2018). National maps have also been recently developed for Canada (Johnston & Flannigan, 2018) and for much of Europe (Modugno, Balzter, Cole, & Borrelli, 2016). Other examples are region specific, including the Mediterranean (Alcasena, Evers, & Vega-Garcia, 2018; Chas-Amil, Touza, & García-Martínez, 2013; Lampin-Maillet et al., 2010), Australia (Gill, Stephens, & Cary, 2013; Price & Bradstock, 2014), and South America (Argañaraz et al., 2017).

General principles for addressing wildfire risk within and around the WUI are well documented (Calkin, Cohen, Finney, & Thompson, 2014; Schoennagel et al., 2017). Discouraging future development limits future exposure (Alexandre, Stewart, Keuler, et al., 2016; Syphard, Bar Massada, Butsic, & Keeley, 2013) while planning codes shape the processes by which subdivision and development occur (Headwaters Economics, 2016; Syphard et al., 2013). Hazardous fuel treatments and prescribed burns reduce fuel loads, which in turn changes fire behavior and allows wildfires to be better managed (North, Stephens, et al., 2015; OIG, 2016). Removing flammable vegetation surrounding structures and updating building standards decreases the chance of loss when exposure does occur (Cohen, 2000; Gibbons et al., 2012; Syphard, Brennan, & Keeley, 2014).

The exact suite of viable mitigation actions, however, will vary with community and landscape (Alexandre, Stewart, Mockrin, et al., 2016; Moritz et al., 2014). For instance, the effectiveness of fuels reduction programs is questionable in certain vegetation types (e.g., Cohen, 2010) and may be ecologically inappropriate in others (Schoennagel, Veblen, & Romme, 2004). In other situations, effective risk mitigation actions (e.g., fuel breaks, prescribed burns, vegetation removal, etc.) may not be socially palatable (Steelman & Burke, 2007) or cost-effective (e.g., when structure density is low or access is limited). Communities further differ in their tolerance of wildfire risk (McCaffrey, 2004, 2008) and in their trust in formal authorities to coordinate risk mitigation efforts (Paveglio et al., 2015). Many fire protection districts lack the personnel or resources to proactively address exposure at a local level, especially where development is low density or isolated. Steep hillslopes can limit both pre-suppression and suppression activities (North, Brough, et al., 2015).

Mitigation strategies need to address factors linked to community exposure at multiple scales. In the western US, for instance, a substantial portion of community wildfire exposure is linked to public lands surrounding communities, including land managed by the US Forest Service (Ager et al., 2017). For these communities, exposure is tied to large landscape-scale properties such as land ownership, ignition patterns, and fuel conditions distant from the urban interface. At the same time, vegetation and development patterns within the WUI directly shape the conditions under which structures are exposed to fire and wildfire losses are most likely to occur (Alexandre, Stewart, Keuler, et al., 2016; Gibbons et al., 2012; Syphard et al., 2014). Furthermore, most applications of the WUI only consider the spatial relationship between development and wildlands, which fails to account for the specific mechanisms by which these two land types relate to each other. This deficiency is particularly striking considering the degree to which wildfire activity can vary by region. Ignoring wildfire transmission can lead to management prescriptions that are focused exclusively on the wildland or interface, thereby negating transboundary risk linkages (Sjostedt & Linnerooth-Bayer, 2001) and contributing to scale mismatches in planning (Cumming, Cumming, & Redman, 2006) and risk governance (Lidskog, Soneryd, & Uggla, 2010; Steelman, 2016).

Matching risk mitigation to varying context and scale requires cohesive planning. This can be seen in the recent US National Wildfire Cohesive Strategy (USDA and USDI, 2018), which emphasizes the need for integration of social and biophysical aspects of risk (Fischer, Spies, et al., 2016; Moritz & Knowles, 2016) and increased collaboration across boundaries (OIG, 2016). As the largest bearer of federal costs for both pre-suppression and suppression (Calkin, Thompson, & Finney, 2015), the US Forest Service (USFS) maintains a pivotal role in implementing the Cohesive Strategy, especially given that wildfire represents one of the agency's most effective tools for restoring and maintaining resilient forests (North, Stephens, et al., 2015; Schoennagel et al., 2017). Systematically characterizing risk at both community and landscape scales allows large land managing agencies like the USFS to accommodate wildfire within diverse transboundary fire regimes (Ager et al., 2017).

In this paper, we characterize community wildfire risk from fires originating on national forests of the western US. We organize community exposure into risk archetypes based on community and forest conditions known to influence wildfire behavior and constrain mitigation strategies at both community and landscape scales. We improve on existing community wildfire risk typologies by joining ‘in-situ’ conditions near threated homes (c.f. Lampin-Maillet et al., 2010) with ‘ex-situ’ conditions where many large wildfire originate (Ager et al., 2017). Finally, we discuss how community wildfire exposure archetypes advance the development of cross-boundary, socio-ecological frameworks for risk management (e.g., Steelman, 2016) and how such a framework can be used to adapt the national wildfire strategy to local conditions. This work addresses key gaps in current wildfire planning including: (a) inadequate characterization of exposure to large fires; (b) one-size fits all approaches to mitigating fire hazard; and (c) definition of scales applicable to management of socio-ecological fire systems.

2. Methods

The following section describes how wildfire exposure was estimated and characterized among communities of the western US. We combined a national dataset of simulated wildfires and a national map of the WUI in the western US to (a) identify areas of national forest that expose communities to wildfire; (b) identify areas of communities where that exposure is greatest, and; (c) classify wildfire exposure of affected communities based on factors known to affect wildfire behavior and constrain management at both community and landscape scale.

2.1. Study area

We examined community exposure to wildfire igniting on national forests within the 11 states of the western US using structure counts derived from 2010 SILVIS WUI data (Radeloff et al., 2005, 2017). Communities were defined using official Census-Designated Places (CDP), which are designated geographic areas used to identify concentrations of populations for statistical purposes (Bureau of the Census, 2008). 5118 CDPs are found in the western US. Structures outside of CDP boundaries were assigned to the nearest CDP based on a 45-minute drive-time. Drive-times were estimated by applying the cost allocation tool in ArcGIS Desktop 10.3 to the North America Detailed Streets dataset (ESRI, 2012). While forty percent of structures (10.8 million) in the dataset were classified as intermix or interface WUI (Radeloff et al., 2005), it is important to note that exposure is still possible in non-WUI classified areas. The median community contained 97 WUI or non-WUI polygons with a median polygon size of 2.4 ha. California (CA) had the greatest number of communities (30%), followed by Washington (WA, 12%), Colorado (CO, 9%), Arizona (AZ, 9%), New Mexico (NM, 9%), Oregon (OR, 7%) and Montana (MT, 7%), Utah (UT, 6%), Idaho (ID, 5%), Wyoming (WY, 4%) and Nevada (NV, 3%). Communities varied in size from ten structures to more than a half million (San Diego, CA, Phoenix, AZ, Los Angeles, CA) with a median of 890.

2.2. Simulation exposure to communities

Our analysis relied on a national 'lib of possible wildfires perimeters developed in 2014 by the USFS Missoula Fire Science Laboratory

(Short, Finney, Scott, Gilbertson-Day, & Grenfell, 2016). The dataset contains several million wildfires representing tens of thousands of hypothetical fire seasons under current conditions. Fire seasons were constructed on the historical relationship between historical fire size, weather conditions, and energy release component (ERC) (Finney, McHugh, Grenfell, Riley, & Short, 2011). Their simulations were performed on 2012 LANDFIRE data describing topography, fuels and vegetation structure at a 270 m resolution (Rollins, 2009). Ignition points were randomly distributed. Fuel moisture levels, ignition density, ignition timing, and wind speed were built using streams of weather data pulled from a national network of weather stations. Simulated fire size distributions were validated against observed distributions and were statistically adjusted to account for the effect of fire suppression (Finney, Grenfell, et al., 2011; Finney, McHugh, et al., 2011).

We limited our analysis to those FSIM wildfires that ignited on national forests and burned into western US communities (as defined using census designated places), which resulted in a data subset of 367,000 fire perimeters (out of approximately 2 million records). Housing unit (HU) exposure for each fire was calculated using the geometric intersection of fire perimeters with polygons from the SILVIS WUI dataset that contained structures. Fig. 1 shows the perimeters of two wildfires that burn into an adjacent community, which is divided into polygons according to development density. The intersection of each fire with the community results in a set of intersected polygons. If W_n represents the set of polygons for fire *n*, the exposure (HU) resulting from fire *n* is

$$e_n = \sum_{i=1}^{W_n} A_i d_i$$

where A_i is the area (ha) of the intersected polygon and d_i is the density of structures (HU ha^{-1}). The combined exposure an entire community therefore represents the sum of exposure for all fires intersecting that community. Since wildfires represent thousands of potential fire seasons, the annual exposure (HU yr^{-1}) for community j is

$$e_j = \sum_{n=1}^{F_j} \frac{e_n}{s}$$

where F_j is the set of exposure values (HU) for community *j* and *s* is the number of total number of seasons simulated (yr). The annual community exposure (HU yr^{-1}) reflects the average number of structures within a community that are exposed to wildfire from national forests each year.

Initial screening of exposure data indicated that 2560 communities in the study area received at least some exposure to fire from the national forest. Given the skewed distribution of wildfire exposure among communities, we constrained our analysis to the top 20% (n = 516). The top 20% of communities collectively accounted for 80% of the annual structure exposure, and each of these communities had an estimated annual exposure greater than or equal to 1.0 HU yr^{-1}. Selected communities were found in all 11 states of the study area and most densely clustered in southern CA, the northern Sierra of CA, the western valleys of MT, the Wasatch front of UT, and the central plateau in AZ.

2.3. Characterizing wildfire exposure

Community exposure was characterized using attributes known to affect potential fire exposure and hazard (Table 1), including development density (HU ha^{-1}), canopy cover (%), conditional flame length (CFL – m), slope (%), fuel models (Scott & Burgan, 2005), restoration needs (i.e., vegetation departure), and management constraints. For simplicity, fuel models were grouped into four classes: grass/shrub fuels, shrub fuels, forest fuels, and other. Agricultural lands were included to distinguish fires in natural grass/shrubland from agricultural fields, where fire behavior is mediated by crop management and irrigation. Information on development density and WUI classification was taken from SILVIS WUI attributes and included WUI type (intermix, interface) and structure density (low, medium, high). We included the majority fire regime (FRG) to identify fire-adapted ecosystems within the national forest (i.e., FRG1 & FRG3, see Rollins, 2009). Finally, we identified protected areas where access for mechanical fuel treatments is restricted (USGS Gap Analysis Program, 2016).

These variables were used to construct a multivariate description of community exposure based on the characteristics of (a) the 100-hectare area immediately surrounding each ignition point and (b) the area of the WUI intersecting the wildfire perimeter (refer to Fig. 1). These variables were then averaged across all fires that reached the community as weighted by the magnitude of HU exposure. Thus, the exposure-weighted average value for variable $\bar{x}$ of community *j* is

$$\bar{x}_j = \sum_{n=1}^{F_j} e_n x_n \Big/ \sum_{n=1}^{F_j} e_n$$

where x_n is the fire-specific value for either (a) the areas surrounding the point of ignition within the national forest or (b) the exposed area of the community, and e_n represents the magnitude of exposure resulting

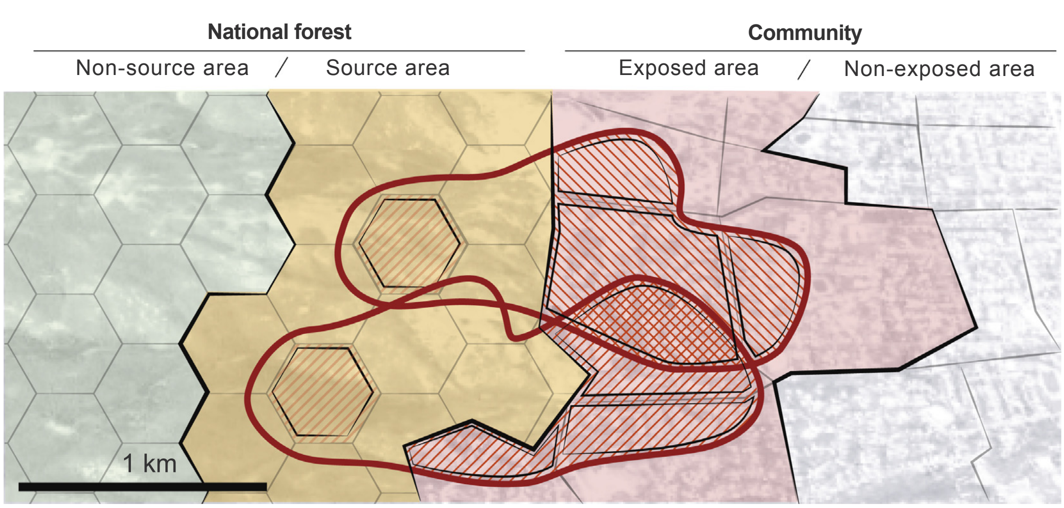

Fig. 1. Community wildfire exposure was determined using the area where wildfire and development intersect (red-hashed area). The archetype of community exposure was based on conditions within both source area where wildfire ignited (yellow-hashed area) and the exposed area of the community (red hashed). Conditions for both areas were averaged for the entire community based on thousands of possible wildfires. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Variables used to distinguish nature of wildfire exposure among threated communities. Variables reflect conditions found within the nation forest source area (NF), exposed areas of the community (C), or both (NF/C).

Variable	Zone	Description
Canopy cover (%)	NF/C	Canopy cover can both limit spread but also lead to crowning and spotting. Source: LANDFIRE
Flame length (m)	NF/C	Conditional flame length describes the intensity of the fire and can limit suppression. Source: FSIM
Forested fuel types (%)	NF/C	Fuel models 161–189 contain timber-understory and timber-litter fuels. Source: LANDFIRE
Shrub fuel types (%)	NF/C	Fuel models 141–149 contain woody shrubs and foliage with limited herbaceous fuels. Source: LANDFIRE
Grass/shrub fuel types (%)	NF/C	Fuel models 101–129 contain mixture of grasses and shrubs, including chaparral fuels in SE California. Source: LANDFIRE
Non-burnable fuel types (%)	NF/C	Fuel models < 100 include urban/developed, agricultural, and bare lands. Source: LANDFIRE
Slope (%)	NF/C	Slope amplifies fire spread, influences local winds, and limits access. Source: LANDFIRE
Manageable (%)	NF	Portion of forest that is manageable, i.e., not a protected status where mechanical thinning might be limited or prohibited. Source: PAD
Vegetation departure (%)	NF	Percent difference in successional class from historical reference conditions. Suppression in fire-adapted forest increases departure. Source: LANDFIRE
Low-severity fire (%)	NF	Fire regime group 1. Fire occurred at < 35-year fire return interval, low and mixed severity. Vegetation often fire adapted. Source: LANDFIRE
Mixed-severity fire (%)	NF	Fire regime group 3. Fire historically occurred at 35–200 year fire return interval, resulted in low and mixed severity. Vegetation often fire adapted. Source: LANDFIRE
High-severity fire (%)	NF	Fire regime group 4. Fire historically occurred at 35–200 year fire return interval, replacement severity. Source: LANDFIRE
Infrequent fire (%)	NF	Fire regime group 5. Fire historically occurred at > 200-year fire return interval, any severity. Source: LANDFIRE
Agricultural lands (%)	C	Percent of WUI classified as agriculture or pasture. Agricultural lands are much less likely to carry fire due to intensive management. Source: NLCD
Intermixed WUI (%)	C	Development (density > 1 hu/6.17 km^2) that intersects with wildland vegetation (> 50% cover). Source: SILVIS
Interface WUI (%)	C	Development where wildland vegetation cover < 50% but located < 2.4 km from heavily vegetated area (> 75% wildland vegetation, > 5 km^2). Source: SILVIS
Non-WUI (%)	C	Development not classified as either interface or intermix due to lack of structure density, lack of wildland vegetation, or lack of proximity to wildland vegetation. Source: SILVIS
Percent high density (%)	C	Percent of community exposure from areas with structure density > 741 hu/km^2. Source: SILVIS
Percent medium density (%)	C	Percent of community exposure from areas with structure density > 49.5 hu/km^2. Source: SILVIS
Percent low density (%)	C	Percent of community exposure from areas with structure density > 6.17 hu/km^2. Source: SILVIS

from that fire. Weighting emphasized the community and landscape conditions where exposure most commonly occurred (e.g., at the periphery of the community or national forests). For example, we found that exposure in Wenatchee, WA, occurred in developed areas where the canopy cover averaged 6% and originated in the national forest where the canopy cover averaged 41%, which differs from the average canopy cover for either the community (less) or the greater national forest (more). The resulting dataset contained 516 rows, where each row described the exposure conditions for a single community using the variables listed in Table 1.

2.4. Gradient and cluster analysis of wildfire exposure

The community exposure data were evaluated using principal component analysis (PCA) as implemented in the *psych* package in R (Revelle, 2016) in order to isolate the principal dimensions of community exposure. Variables were scaled before the PCA, and the resulting components were rotated using *varimax* rotation to minimize cross loading of variables and facilitate interpretation (Jolliffe, 2002). We determined the number of components to retain using parallel analysis (O'Connor, 2000). Components were treated as significant when their respective eigenvalues exceeded those generated using a randomly shuffled dataset. Eight components were retained using this criterion, which explained 80.2% of the variance within the exposure data (Fig. 2-A).

Archetypes of community exposure were assigned by clustering on component scores using the PAM algorithm as implemented in the *cluster* package in R (Maechler et al., 2015). Compared to k-means, PAM clusters are less sensitive to outliers and are considered more appropriate for nonparametric data (Kaufman & Rousseeuw, 1990). Since divisive clustering solutions like PAM are sensitive to the initial starting points, we used consensus aggregation to make final archetypes assignments and to report the stability within each archetype (Monti, Tamayo, Mesirov, & Golub, 2003). This bootstrapping procedure calculates cluster solutions for 100 subsamples constructed using 80% of observations randomly sampled from the original dataset with replacement (Fig. 2-B). Communities were grouped according to their most frequent cluster/archetype assignment. The procedure was repeated across a range of cluster numbers and assessed using changes in both cumulative density function curves as well as the change in area under each CDF with each increase of k (see Monti et al., 2003 for a detailed discussion) (Fig. 2-C).

3. Results

3.1. Community exposure to wildfire originating from national forests

Transboundary community wildfire exposure was concentrated within distinct regions found in all 11 states in the western US (Fig. 3). The area of the national forest where community exposure originated (i.e., the source area) represented approximately 10.6 million hectares, or 16% of the total area of all national forests in the western US (66 million hectares). The portion of the national forest that contributed community exposure varied from less than 5% of the forest area (e.g., Gifford-Pinchot, Medicine Bow, or Mt. Baker-Snoqualmie National Forests) to greater than 80% (Angeles, San Bernardino, or Cleveland National Forests). As described above, 80% of wildfire exposure was concentrated among 20% of communities. Within these highly-exposed communities, 60% of the community area accounted for 80% of the total housing exposure. Exposure varied widely among communities. In extreme instances, 5% of the developed area of a community resulted in 80% of house exposure (e.g., where exposure was constrained to specific subdivisions) while in other cases exposure was spread equally across the community. The average distance between ignition points and points of housing exposure was 14.2 km and varied among communities from a low of 2.8 km to a high of 50 km.

Table 2 describes conditions related to exposure for both national forest source areas and exposed community areas among the 516 most highly exposed communities in the western US. On average, the simulated wildfires that burned into the WUI burned at moderate intensity (conditional flame length = 1.8 m), occurred under open canopy cover (22.5%), and were carried by a mixture of forest litter (34.8%), grass (51.7%) and shrub (13%) fuels. Fires generally ignited in fire-adapted forests (63%) that were not restricted from management based on forest

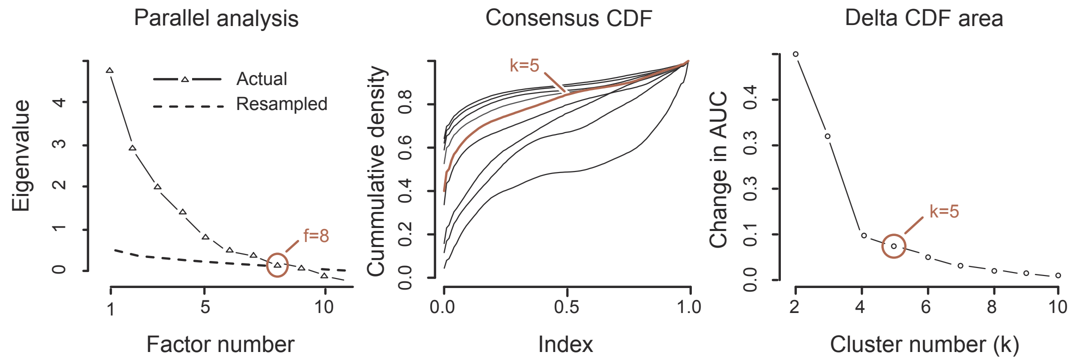

Fig. 2. Community wildfire exposure was grouped into 5 exposure archetypes based on 8 components. The number of components (f = 8) was determined using parallel analysis (left). The number of clusters (k = 5) was chosen based on the change in the area under the curve (right) for successive cumulative density functions (middle).

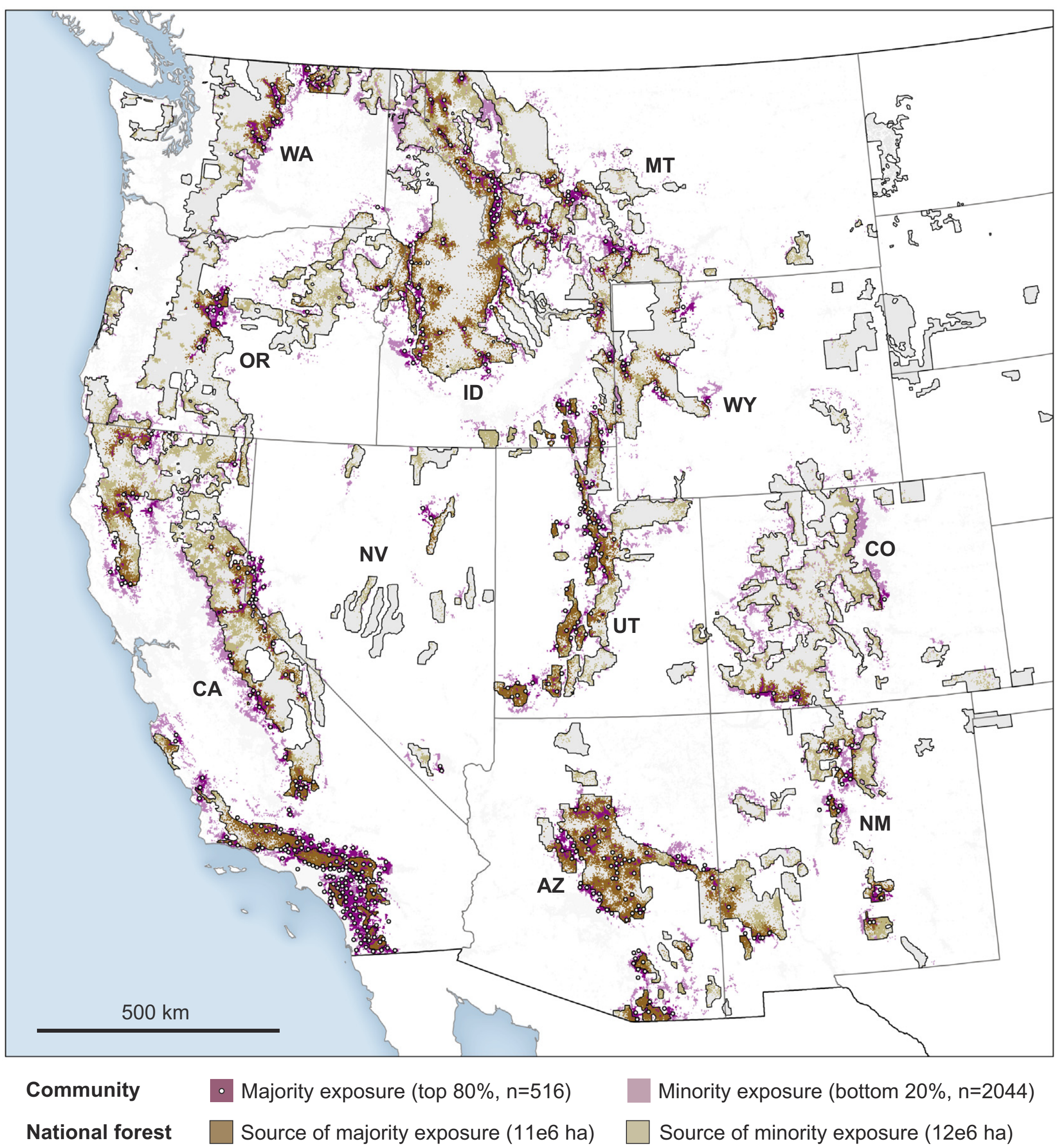

Fig. 3. Map of the western US shows the 516 communities that account for 80% of the wildfire exposure originating in the national forest. The areas of the national forest that contribute the most exposure are shown in orange and the most exposed areas within communities are shown in magenta. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Descriptive statistics of wildfire exposure among highly-exposed communities (n = 516). The reference values represent the average conditions among western national forests and western communities (WUI and non-WUI).

National forest variable	Mean (SD)	Reference	Community variable	Mean (SD)	Reference
Canopy cover	22.5 (12.7)	30.9	Canopy cover	7.4 (8.7)	5.6
Forest fuels	34.8 (25.6)	52.9	Forest fuels	11.1 (15.7)	12.0
Shrub fuels	13.0 (14.9)	6.6	Shrub fuels	9.0 (15.4)	2.7
Grass fuels	51.7 (27.3)	36.5	Grass fuels	54.1 (23.2)	23.4
Non-burnable fuels	0.0 (0.0)	3.9	Non-burnable fuels	25.8 (17.3)	61.8
Flame length	1.5 (0.3)	1.5	Flame length	1.5 (0.4)	0.6
Slope	18.6 (5.8)	16.5	Slope	5.6 (3.7)	2.6
Manageable lands	85.0 (19.0)	76.0	Agricultural lands	5.4 (9.3)	7.5
Vegetation departure	44.2 (12.3)	37.3	Intermixed WUI	50.1 (26.6)	9.7
Low-severity fire	40.2 (31.3)	30.3	Interface WUI	40.2 (26.1)	29.8
Mixed-severity fire	22.8 (28.4)	36.2	Non-WUI	9.7 (14.9)	59.7
High-severity fire	30.6 (28.2)	21.5	High-density development	16.1 (17.5)	65.7
Infrequent fire	6.2 (16.4)	10.4	Med-density development	53.8 (21.2)	27.8
			Low-density development	30.1 (24.5)	0.07

plan standards (85%). Compared to the non-source areas of the national forest, source areas were more open and had a greater portion of grass and shrub fuels. High frequency, low-severity (FRG1) and high frequency, high-severity (FRG4) were more common in source areas, while mixed-severity (FRG3) and infrequent fire regimes (FRG5) were less common. Compared to national forest source areas, exposed portions of the community were much more open (canopy cover = 7.4%), had small amounts of forest and shrub fuels (11.1% and 9% respectively), and had slightly lower fire hazard (conditional flame length = 1.45 m). Compared to the entire community, exposed areas were much more likely to be classified as WUI (either intermix or interface), and tended to occur in areas where housing density was lower, and as a result, had a greater portion of wildland fuels (predominantly grass).

3.2. Variation in conditions among highly-exposed communities

Components retained from the principal component analysis (labeled F1–F8) explained 80% of the difference in character of wildfire exposure among communities (Table 3). Reflecting the diversity of transboundary exposure among communities, variance was widely distributed across the eight components, and no component explained more than 18% of the total variance. Component F1 (18% of variance) related canopy cover to the ratio of forested fuels and grass fuels. Component F2 (17% variance) described the ratio of exposure in communities resulting from intermixed compared to interface development. F2 loadings also showed that interface communities had higher development density with a greater proportion of unburnable fuels while intermix communities had lower density and higher conditional flame length. Component F3 (12% variance) described the correlation between the percentage of shrub fuels and fire hazard. The relative independence in variance between F1 and F2 revealed how vegetation conditions vary widely among WUI classes in different communities. For instance, some communities where a preponderance of exposure occurred in interface WUI were still characterized by the denser and closed vegetation typically associated with intermix WUI.

The remaining five components characterized a smaller degree of differences among exposed communities. Component F4 (9% variance) described management opportunities and constraints in addition to the correlation between vegetation departure from historical conditions and the percent of manageable lands within the national forest. Component F5 (8% variance) showed a relationship between higher slope, canopy cover, forested fuels and absence of grass fuels. Component F6 (7% variance) described low-density exposure coinciding with agricultural/grazing lands with limited forest cover. The final two components described differences in fire regimes within the national forest source area. Component F7 (6% variance) described the communities exposed to fire originated from low-severity or mixed-severity fire regimes. Component F8 (5% variance), by contrast, identified community exposure from low-frequency, high severity fire regimes constrained either by lack of fuels or flammable conditions.

3.3. Archetypes of community wildfire exposure coming from national forests

Community exposure archetypes (labeled C1–C5) represent groups of communities with similar wildfire exposure characteristics (Fig. 4). Archetypes C2 and C4 were most common (n = 147 and n = 153 respectively) while C1 and C5 were least common (n = 49 and n = 58 respectively). Archetypes generally fell along a continuum from low canopy cover dominated by grassy fuels (C1 and C2) to closed canopy cover dominated by forested fuels (C3, C4, and C5). The consensus plot in Fig. 4 shows the portion of times that each of the 516 communities was assigned to each cluster. The final cluster assignment was based on the plurality value. Within-group consensus was highest for archetypes C1, C2 and C5 and lowest for C3 and C4. The dendrogram at the top of Fig. 4 reveals subgroups within each cluster, which are most notable in clusters C3 and C4. Table 4 describes the mean values and standard deviations for the exposure characteristics within each archetype. A brief description of the five primary community exposure archetypes follows.

C1: Infrequent-exposure communities (n = 49)

Archetype C1 communities were defined by low frequency, high severity fires limited by either fuels or flammability. Development in these communities was characterized by low-density and low-slope. Fuels were grass-dominated. The cluster included two distinct geographic pockets: the desert southwest with desert scrub and Mogollon chaparral and interior lodgepole pine and subalpine spruce-fir forests. Communities typifying the former included those surrounding the Phoenix metro area, AZ, while the later included communities of Big Sky, MT, and Jackson Hole, WY.

C2: Open-interface communities (n = 147)

Archetype C2 was most commonly associated with communities in southern California. Exposure in these communities commonly tended to occur in high-density interface development in steep slopes with open forest cover. Fuels represented a mixture of grass and shrubs fuels, including chaparral shrubland. Nearby national forests were open, departed from historical conditions, and frequently management limited. Vegetation in the national forest included chaparral and grassland historically shaped by frequent high severity fires. Communities include

Table 3
Loadings of exposure variables on the 8 components (F1–F8) used to distinguish community archetypes. Components are ordered by the variance explained. Loadings greater than 0.5 are shown in bold while loadings less than 0.1 are omitted. The top panel shows component loadings for variables describing exposure conditions within source areas of the national forest. The bottom panel shows loadings of exposure conditions within community exposure areas.

National forest variable	F1	F2	F3	F4	F5	F6	F7	F8
Canopy cover	**0.9**	0.11				0.11		0.2
Forest fuels	**−0.8**		−0.29		−0.13	−0.24		−0.14
Shrub fuels	**0.84**		-0.18		0.1	0.28		
Grass fuels		−0.13	**0.84**				0.27	0.17
Flame length	−0.29		**0.7**				0.18	0.2
Slope		−0.35	0.15	−0.34	**0.53**	0.27		0.35
Manageable lands	0.1			**0.92**				
Vegetation departure			0.11	**0.88**				0.13
Low-severity fire	0.36	0.18				−0.15	**−0.8**	0.32
Mixed-severity fire	0.41		0.14		−0.2	0.11	**0.81**	
High-severity fire	**−0.74**	−0.25		0.13	0.38			
Infrequent fire	−0.15		−0.13	−0.1	−0.16		−0.12	**−0.85**
Community variable	F1	F2	F3	F4	F5	F6	F7	F8
Canopy cover	**0.65**	0.37		0.11	0.41	−0.29		
Forest fuels	**−0.53**	0.38	**−0.51**		−0.38		0.14	0.17
Shrub fuels	**0.65**	0.19	−0.22	0.14	0.48	−0.22		−0.14
Grass fuels	0.16	0.16	**0.84**		0.11		−0.12	
Non-burnable		**−0.83**	0.13			0.16		
Flame length		0.2	0.13		**0.82**	−0.12		0.14
Slope		**0.61**	**0.57**				-0.18	
Agricultural lands	0.17	−0.17			−0.11	**0.79**	0.21	
Intermixed WUI	−0.13	**−0.86**						
Interface WUI		**0.87**				−0.26		
High-density development		**−0.7**				−0.39	−0.1	
Low-density development	0.14	0.61				**0.59**		
Statistic	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**
SS loadings	4.36	4.10	2.76	1.83	1.79	1.62	1.58	1.21
Proportional variance (%)	0.18	0.17	0.12	0.08	0.07	0.07	0.07	0.05
Cumulative variance (%)	0.18	0.35	0.47	0.54	0.62	0.69	0.75	0.80

Las Angeles, CA, Sedona, AZ, and Boise, ID.

C3: Mixed-interface communities (n = 109)

Archetype C3 was the most varied of the five archetypes. Vegetation contained a mixture of forested, grass and shrub fuels. Communities were largely unforested, while source areas contained open canopy mixed-conifer forests (ponderosa pine, pinyon-juniper, Douglas-fir). The exposure type was common throughout the western US, including moderate elevation communities of the SW and Great Basin regions. Typical communities included Bend, OR, Reno, NV, Flagstaff, AZ, and Santa Fe, NM. Some communities in C3 were similar to those in C2 and C4.

C4: Forested-intermix communities (n = 153)

Archetype C4 described communities with low-density development intermixed within a matrix of forest and agricultural lands; national forest source areas had high canopy cover and were adapted to historically low or mixed-severity fire. The archetype was common to the Northern Rockies, and communities on the east side of the Cascade/Sierra ranges, and higher mountainous areas of the SW. Communities of C4 had the lowest-density development and the highest community canopy cover of all archetypes. National forests were predominately Douglas-fir and ponderosa pine and to a lesser extent shrubland steppe. Typical communities included Colorado Springs, CO, Leavenworth, WA, Lolo, MT, Squaw Valley, CA, and Ruidoso, NM. Some C4 communities were similar to C3.

C5: Shrub-interface communities (n = 58)

Archetype C5 was found primarily in communities along the Wasatch Front where moderate density interface development occurred in areas with steep slopes. Forests had a mixture of low canopy-height trees and shrubs growing under conditions of wet springs and hot, dry summers. National forests contained pinyon-juniper woodland, Bigtooth Maple, Douglas and Grand-fir, and aspen forests. The combination of fuels and topography led to more common higher intensity burns. Example communities included Salt Lake City, UT, Bountiful, UT, and Elko, NV.

4. Discussion

We have shown how conditions contributing to community wildfire exposure differed markedly among communities in the western US, primarily with regards to forest cover, fuels, and development patterns, and secondarily with regards to conditions that either facilitate or hinder mitigation actions. While federal wildland fire policy in the US fosters a diversified approach to managing wildfire risk (e.g., promoting fire-adapted communities, restoring fire-resilient landscapes, and ensuring safe and effective wildfire response), it provides only limited guidance on how these policy goals can be translated into contextually-relevant strategies (Wildland Fire Leadership Council, 2014). The five archetypes of community exposure that we identified illustrate the need to match risk mitigation strategies to specific conditions that characterize a spectrum of transboundary risk contexts (Fig. 5). For example, expanding hazardous fuel treatments and prescribed burns are more likely to be effective and ecologically appropriate in exposure archetype C3 and C4 (North, Stephens, et al., 2015; OIG, 2016). In other cases, such as exposure archetype C2 and C5, mitigation efforts should focus more on the areas within and nearby development, which includes restricting development in fire-prone wildlands (Headwaters

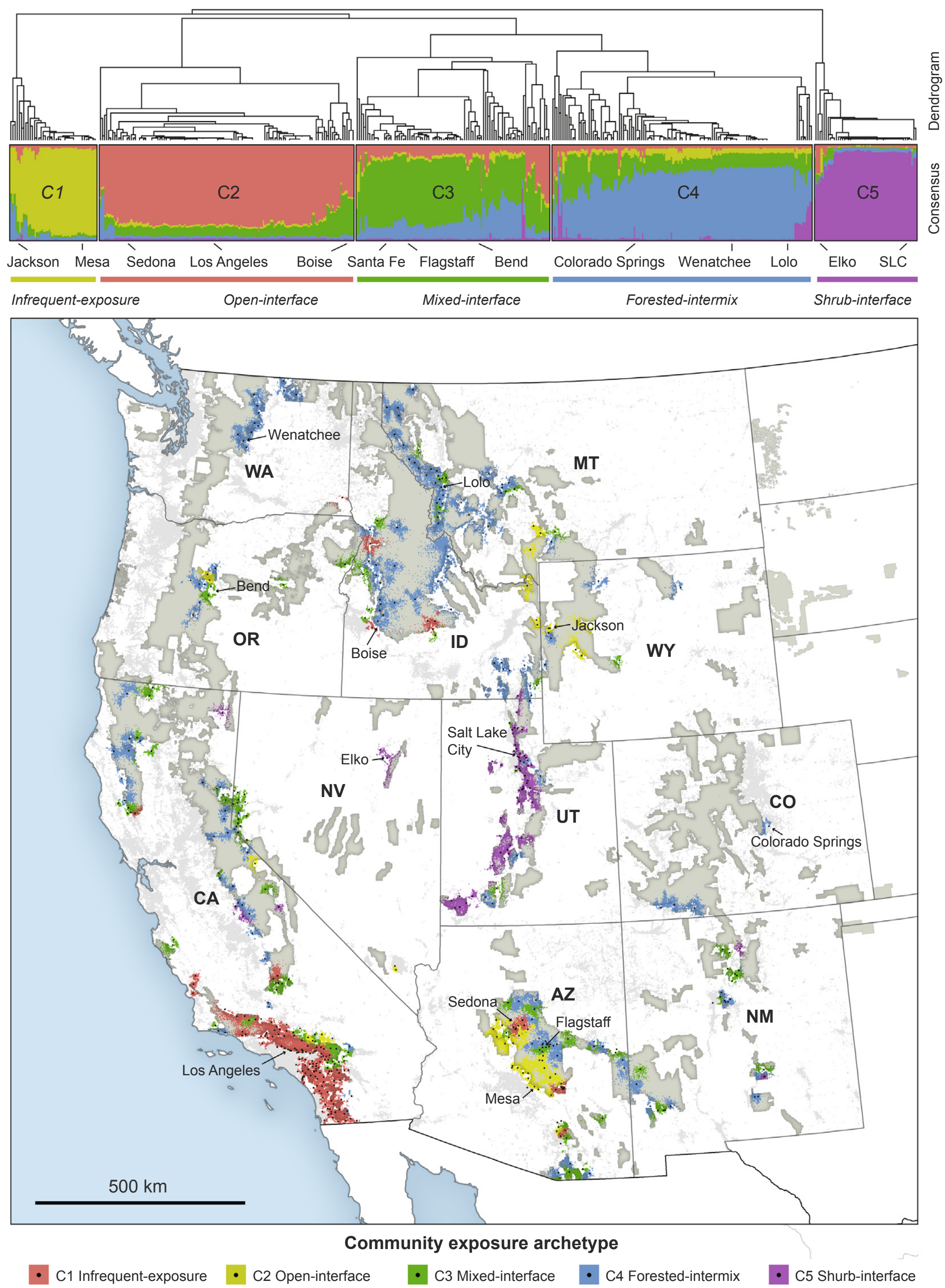

Fig. 4. Exposure patterns for highly-exposed communities divided into five archetypes, as shown in the dendrogram and consensus plot above and in the map below. Differences in the height of branches in the dendrogram reflect differences within and among clusters. Branches of the dendrogram dominated by a single color in the consensus plot represent greater homogeneity among communities within archetypes (e.g., C2 open-interface), while branches containing a mixture of colors represent groupings that are less distinct.

Economics, 2016) and reducing flammable vegetation surrounding homes (Gibbons et al., 2012). Improving community-based disaster planning and response (Calkin et al., 2014) may be particularly important in exposure archetype C5 due to shrub fuels, steep slopes, and high flame lengths, as observed both within the national forest source areas and exposed areas of the community. Our research also points towards the importance of strategic coordination among jurisdictions that share transboundary risk.

4.1. National forest sources areas

Most federal wildfire risk mitigation actions fall on publicly managed lands outside of designated WUIs (Schoennagel, Nelson, Theobald, Carnwath, & Chapman, 2009). While extensive, the source of community wildfire exposure typically represented only between 10% and 30% of most national forests (although some forests in southern California exceed 50%). Many of the highly-exposed communities that we

Table 4
Descriptive statistics show differences in the character of exposure among 5 community archetypes, represented as mean values and standard deviations (top panel: nation forest source areas, bottom panel: community exposure areas).

National forest variable	C1 Condition limited	C2 Open interface	C3 Mixed interface	C4 Forested intermix	C5 Shrub interface	Overall
Canopy cover	24 (10.2)	12.3 (5.8)	31.5 (10.3)	11 (12)	30.9 (9.7)	22.5 (12.7)
Forest fuels	36 (22.4)	18.6 (13.7)	53.4 (23.3)	22.1 (34)	35.7 (18.4)	34.8 (25.6)
Shrub fuels	10.1 (11.2)	16.4 (11.6)	5 (8.4)	3.4 (5)	39.4 (14.7)	13 (14.9)
Grass fuels	53.3 (22.2)	64.8 (19.5)	41.1 (23.4)	74.1 (33.4)	24.4 (22.1)	51.7 (27.3)
Flame length	1.7 (0.3)	2.0 (0.2)	1.8 (0.2)	1.6 (0.2)	2.2 (0.3)	1.8 (0.3)
Slope	17.4 (6.1)	21.6 (4.6)	17.1 (5.4)	13.8 (4.2)	21.4 (5.4)	18.6 (5.8)
Manageable lands	84.0 (22.7)	81.3 (18.6)	82.3 (21.9)	91.5 (13.1)	82.5 (20.1)	85.0 (19.0)
Vegetation departure	40.0 (14.3)	43.9 (13.0)	42.8 (12.3)	45.0 (10.1)	48.7 (12.4)	44.2 (12.3)
Low-severity fire	65.2 (21.8)	31 (20.1)	53.1 (32)	11.2 (16.7)	6.8 (15.3)	40.2 (31.3)
Mixed-severity fire	16.4 (18)	2.9 (7.5)	29.2 (24.5)	14.1 (18.3)	76.2 (21.4)	22.8 (28.4)
High-severity fire	15.9 (13.6)	65 (20.7)	15.4 (16.3)	26.1 (22.1)	14.6 (16.1)	30.6 (28.2)
Infrequent fire	2.3 (6)	1 (2.8)	1.9 (6)	48.6 (24.7)	2.4 (3)	6.2 (16.4)
Community variable	**C1 Condition limited**	**C2 Open interface**	**C3 Mixed interface**	**C4 Forested intermix**	**C5 Shrub interface**	**Overall**
Canopy cover	4 (4.8)	4.3 (5.9)	13.8 (10.3)	2.3 (3.7)	9.4 (8.3)	7.4 (8.7)
Forest fuels	5.6 (8.2)	6.6 (13.3)	22.8 (19.4)	5.7 (11.6)	6.4 (7.3)	11.1 (15.7)
Shrub fuels	8 (14.2)	7.3 (11)	6.3 (13.7)	4.9 (13.9)	26.3 (20.7)	9.0 (15.4)
Grass fuels	55.4 (20.8)	53 (20)	55.5 (24.8)	70.3 (23.1)	37.2 (19.6)	54.1 (23.2)
Non-burnable	31.1 (16.9)	33.1 (15.7)	15.4 (13.1)	19.1 (17.2)	30.2 (17.3)	25.8 (17.3)
Flame length	1.5 (0.4)	1.4 (0.3)	1.3 (0.4)	1.6 (0.4)	1.7 (0.6)	1.5 (0.4)
Slope	3.5 (1.9)	7.2 (3.8)	6.3 (3.5)	3 (1.7)	5.8 (4.6)	5.6 (3.7)
Agricultural lands	4.1 (7.1)	2.7 (6.5)	6.9 (10.3)	3.8 (9.4)	11.9 (12.3)	5.4 (9.3)
Intermixed WUI	43.3 (22.6)	39.4 (23.2)	66.1 (24)	58 (25.7)	41.4 (27.1)	50.1 (26.6)
Interface WUI	47.2 (21.3)	52.3 (24.6)	22.6 (20)	33 (23.9)	49 (27.7)	40.2 (26.1)
Non-WUI	9.5 (14.8)	8.3 (17.2)	11.3 (11.9)	9 (19.3)	9.7 (11.4)	9.7 (14.9)
High-density development	21.8 (18.7)	24.2 (18.8)	6.3 (8)	16 (19.5)	10.7 (14.2)	16.1 (17.5)
Med-density development	56.2 (17.8)	57 (20.2)	45.3 (22.1)	56.1 (20.1)	61.4 (21.5)	53.8 (21.2)
Low-density development	22 (16.3)	18.8 (20.2)	48.3 (24.2)	27.9 (21.3)	27.9 (23.3)	30.1 (24.5)
Count (n)	49	147	109	153	58	516

examined received fires from areas of the national forest where mechanical thinning, slash removal, and prescribed fires are suited to reduce wildfire size and severity (Stephens et al., 2012) and improve the capacity of managers to contain or suppress fires when needed. Despite valid concerns regarding the ecological impact of fuel reduction programs in some forest types (e.g., Schoennagel & Nelson, 2011), our results suggest that the areas of the national forest most likely to threaten communities tend to be lower-elevation, drier, open-structure mixed-conifer forests (Table 2). Such conditions tend to support fuels treatments that restore forest structure at the same time as reducing fire hazard to communities. On the other hand, as much as a third of community wildfire exposure originated on parts of the national forest where thinning and prescribed burns are less viable. This include community exposure from sparsely forested or non-forested lands where fire is carried either by fine-fuels dependent on inter-annual fluctuations in precipitation (Littell, Mckenzie, Peterson, & Westerling, 2009) or where fire ecology is characterized by high-severity and rapid regeneration of fuels (Keeley, Syphard, & Fotheringham, 2008). We further found that while community wildfire exposure typically came from national forests with relatively frequent fire return intervals, 10%

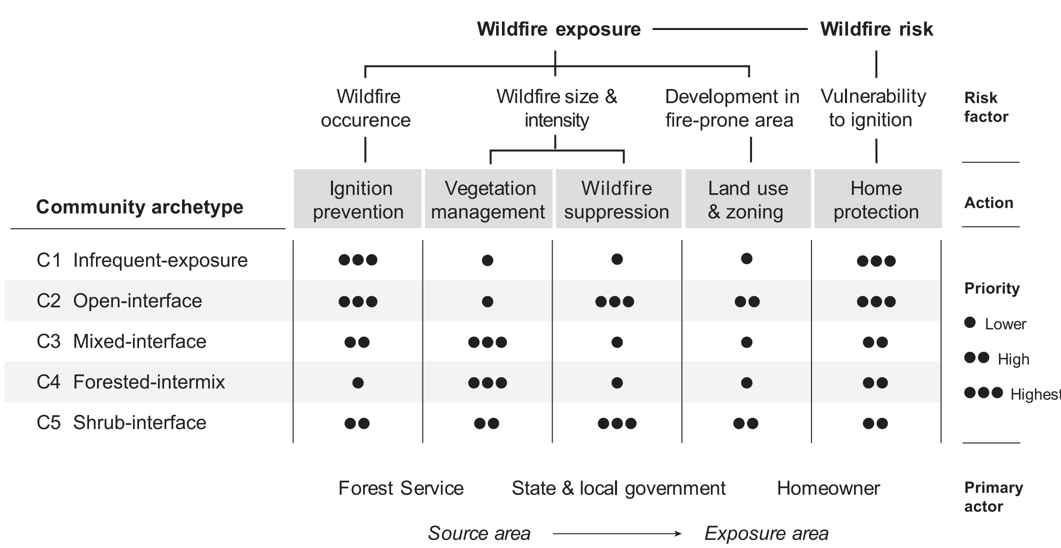

Fig. 5. Community archetypes reflect different priorities for managing wildfire risk. Vegetation management, for instance, is effective in only half of highly-exposed communities (i.e., C3 mixed-interface and C4 forested-intermix communities). Differences in prioritization also indicate different needs for cross-boundary coordination and which actors are involved.

of highly-exposed communities were notable for the longer wildfire return intervals constrained by either lack of fuels (e.g., Mogollon foothills in AZ) or climatic conditions that typically limit flammability (e.g., the greater Yellowstone ecoregion of WY and MT). We found surprisingly little difference among communities regarding manageability (generally high) and vegetation departure from historical condition (generally moderate) in national forest source areas. Compared to the national forest as a whole, source areas were less likely to be protected and more likely to be ecologically departed from historical conditions.

4.2. Community exposure areas

Our results confirm that community exposure to wildfire differs markedly with development patterns (Hammer, Stewart, & Radeloff, 2009). Half of estimated exposure occurred in low to moderate density intermixed development, much of which has likely occurred in jurisdictions that lack strong controls on development (Burby, 2006). These fire-prone regions often find themselves in a vexing mitigation paradox where the threat of wildfire exposure to low-density development is at odds with economic incentives to promote growth (Moritz et al., 2014; Steelman, 2008). The extent of exposure within intermix WUI lends to the scale mismatches that challenge existing wildfire risk governance (Burby, 2006; Cumming et al., 2006; Steelman, 2016). Nonetheless, land-use planning remains key to limiting wildfire exposure trends over time (Moritz et al., 2014; Nielsen-Pincus et al., 2010; Syphard, Keeley, Massada, Brennan, & Radeloff, 2012) and a growing number of fire-prone areas are implementing WUI-specific building and land subdivision codes (Headwaters Economics, 2016). Mitigating exposure of transboundary wildfire risk requires collaborative engagement among both organizations responsible for managing wildfire risk and others that may influence the behavior of actors on either side of the risk transmission boundary (Jakes et al., 2011; Williams et al., 2012). Without coordination, risk mitigation is less likely to address shared priorities and more likely to be rendered ineffective due to indirect spillover effects (Abrams et al., 2015; Fischer & Jasny, 2017). Many fire-prone regions in the western US are pioneering adaptive approaches to risk mitigation through wildfire learning networks, which provides a forum for communities to share and discuss local risk mitigation actions (Goldstein, Butler, & Hull, 2010) and Fire Adapted Communities programs that connect wildfire education, planning, and action with comprehensive resources (Fire Adapted Communities Coalition, 2014). The community exposure archetypes described in this article support these networks by identifying communities that face similar challenges and can draw on similar strategies to becoming fire-adapted.

4.3. Connecting multiple scales of exposure

Our work contributes a spatial planning framework for transboundary wildfire risk mitigation that defines specific geography encapsulating where people live, the local and *ex-situ* risk drivers, and the multi-party cooperation needed to manage the problem, all of which contribute to community and wildland resilience. Existing schemes for classifying wildfire risk rely solely on structure location and surrounding vegetation cover (e.g., Bar-Massada, Stewart, Hammer, Mockrin, & Radeloff, 2013; Chas-Amil et al., 2013; Lampin-Maillet et al., 2010). Focusing exclusively on conditions within the WUI ignores the scale of wildfire risk transmission (Ager et al., 2017), which is important both because of the larger landscape context and contrasting organizational stances towards wildfire risk (Steelman, 2016). By defining the WUI according to both the biophysical and built factors of communities and their surrounding landscape, we have provided an expanded definition of WUI that supports efforts to link the biophysical and social factors that underlie wildfire risk exposure (Ager, Kline, & Fischer, 2015; Moritz et al., 2014; Spies et al., 2014). Our results make clear that aspects of exposure vary greatly both within and among communities. From the perspective of federal land managing agencies, this expanded definition provides specific guidance over where and how federal dollars are best spent, and points to opportunities for drafting agreements between communities, private landowners, and state or federal land managers that can better leverage their mutual interests (Fig. 5).

4.4. Limitations and future research

Geographic inventories of development and infrastructure fail to address the institutional and social dimensions of communities that define their capacity to anticipate, prepare for, and mitigate wildfire hazards (Fischer, Vance-Borland, Jasny, Grimm, & Charnley, 2016; Spies et al., 2014). Individual communities are likely to establish different strategies for planning, mitigating, and recovering from wildfire (Paveglio et al., 2015), and many of these will be tied to their geographic and social context, their understanding of ecosystems processes, and their relationship with federal agencies (Paveglio, Carroll, Stasiewicz, Williams, & Becker, 2018). Additional data on community willingness and capabilities to mitigate wildfire risk need to be brought into the process of adapting to wildfire (Fischer, Spies, et al., 2016; Nielsen-pincus, Ribe, & Johnson, 2015). Combining biophysical and social archetypes is an important next step in future research in addition to the integrated management of fire systems (Ager et al., 2015).

The scope of this analysis was limited to national forests to address the immediate policy void concerning expanded fuels funding appropriated to the USFS, but as a result, it excluded exposure originating outside of the national forest system, such as fires igniting within community boundaries, or on other private, state, or other federally managed lands. The risk of community wildfire exposure is limited for most national forests, and focusing management on source areas where wildfire exposure originates will have the greatest impact on reducing community wildfire risk. Still, wildfire transmission from national forests into communities represents only a portion of the total fire exchanged among the land tenures most common to the western US (Ager et al., 2017). For instance, highly-exposed communities were notably absent from Colorado within our study, which indicates that community risk in the state is more likely to come from other land tenures. An expansion of our analysis to all lands is necessary to understand the nature of wildfire exposure across all communities in the western US. As a final point, the scale at which we examined community exposure (i.e., the entire western US) meant that we did not describe the mapped extent of source and exposure areas in detail. This is likely to be a task better suited for smaller scales of study, such as in those regions where community wildfire exposure was spatially concentrated. Defining the specific spatial extent of source and exposure areas within these regional exposure ‘hotspots’ is a clear direction for future work.

While this analysis was specific to the western US, the implications of our work are germane to other fire-prone regions globally. As more fire-prone regions incorporate detailed maps of the WUI into wildfire risk mitigation programs (e.g., Bowman et al., 2011; Lampin-Maillet et al., 2010), it is important that those mitigation programs be implemented in a way that does not artificially “flatten” the complex social and biophysical context that underlies wildfire risk. The diversity of conditions we reported is likely true for other contexts globally, and since the increased risk of wildfire found in many fire-prone regions will likely outstrip available resources, it is critical that mitigation actions be tied to a cohesive risk management strategy that accommodates diversity and scale.

5. Conclusion

The risk planning problem faced by land and fire management agencies across the globe involves a diversity of local contexts. Given the scale of the wildland urban interface in the western US, along with changes in fire activity expected from a changing climate, the need to strategically plan and implement mitigation actions at a landscape scale is critical. Hazardous fuel investments can be rendered ineffective given the convoluted process of appropriating funds, distributing money, tying investments to existing programs and planning efforts, and implementing them on the ground. Community exposure archetypes constructed on an expanded definition of the WUI that explicitly considers the scale and process of wildfire exposure can help match national wildfire policy to the diversity of local community contexts.

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