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Research Paper

Social vulnerability to large wildfires in the western USA

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A B S T R A C T

Federal land managers in the US can be informed with quantitative assessments of the social conditions of the populations affected by wildfires originating on their administered lands in order to incorporate and adapt their management strategy to achieve a more targeted prioritization of community wildfire protection investments. In addition, these assessments are valuable to socially vulnerable communities for quantifying their exposure to wildfires originating on adjacent land tenures. We assessed fire transmission patterns using fire behavior simulations to understand spatial variations across three diverse study areas (North-central Washington; Central California; and Northern New Mexico) to understand how different land tenures affect highly socially vulnerable populated places. Transboundary wildfire structure exposure was related to populations with limited adaptive capacity to absorb, recover and modify exposure to wildfires, estimated with the Social Vulnerability Index using US Census unit data (block groups). We found geographic heterogeneity in terms of land tenure composition and estimated fire exposure. Although high social vulnerability block groups covered small areas, they had high population and structure density and were disproportionately exposed per area burned by fire. Structure exposure originated primarily from three key land tenures (wildland-urban interface, private lands and national forests). Federal lands proportionately exposed, on an area basis, populated places with high social vulnerability, with fires ignited on Forest Service administered lands mostly affecting north-central Washington and northern New Mexico communities.

1. Introduction

The recent death toll from wildfires in Greece (2007, 2018), Australia (2009), Portugal (2017) and California (2017–18) reveals how the most socially vulnerable people are disproportionately affected when fire strikes. Two thirds of the 44 victims in the 2017 Northern Californian fire were older than the age 65 (Emslie, 2017). Of the 100 people who perished in a single 1400-hectare fire event outside Athens, Greece (2018), 11 were children and minors and 45 were elders (Goldammer, Xanthopoulos, Eytixidis, Mallinis, Mitsopoulos, & Dimitrakopoulos, 2019). Ten years earlier in Greece (2007), fires killed 84 people in mostly rural areas with lower income populations (Xanthopoulos, Viegas, & Caballero, 2009). During the 2017 wildfires in Pedrógão Grande, Portugal, 47 of the 66 victims were found in or near their cars while trying to escape (Klepsvik, 2018). Of the 173 dead during the 2009 Black Saturday fires in Australia, 118 perished while sheltering in structures (Blanchi, Whittaker, Haynes, Leonard, & Opie, 2018), with 13% of all victims aged less than 18 (a substantial majority were under 15) and 16% aged 70 or over (Teague, McLeod, & Pascoe, 2010). These incidents revealed that differences in social vulnerability, defined as the adaptive capacity to absorb, recover and modify exposure to wildfires (Davies, Haugo, Robertson, & Levin, 2018), can affect the magnitude and duration of impacts like the loss of property, livelihoods, or services. Those hazards become disasters specifically when they affect socially vulnerable populations.

In most fire-prone countries across the globe, the responsibility for managing wildfire risk fall on government agencies, which administer or manage large tracks of wildlands and tend to quantify risk to inform management decisions in terms of structure exposure or loss of resources. Recent disasters highlight the need for expanding these metrics by looking at the interaction between the biophysical dimensions of wildfire exposure (i.e. land tenure composition and parcel geometry, topography, fuel models, fire regimes, disturbances and past management effects), and the social dimensions of vulnerability (Keeler et al., 2019).

Gaining insights on social-ecological fire-related interactions can help government agencies prioritize fuel management efforts and reduce fire risk from government (local, state or federal) administered lands to socially vulnerable and underprivileged populations. Previous research has highlighted the need for a coupled analysis of social and biophysical factors in community wildfire protection planning, and the benefits of such an approach include overcoming temporal and spatial

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scale mismatches in risk mitigation (Ager, Kline, & Fischer, 2015), understanding social-ecological feedbacks and human adaptation in fire-prone landscapes (Spies, Scheller, & Bolte, 2018; Spies et al., 2014), promoting learning among different scales of actors throughout the governance system to support the complexity necessary to match the wildfire problem (Steelman, 2016), identifying specific social vulnerabilities and trade-offs (McLennan & Eburn, 2015), and facilitating adaptation strategies across widely varying public and private landscapes (Moritz et al., 2014). The extensive literature on social science related to wildfire issues (McCaffrey, 2015) has studied risk perception, mitigation decisions and perceived consequences (Champ & Brenkert-Smith, 2016; Champ, Donovan, & Barth, 2013; Dickinson, Brenkert-Smith, Champ, & Flores, 2015; Gordon, Luloff, & Stedman, 2012); community pre-fire mitigation (Cohn, Williams, & Carroll, 2008) and adaptive capacity (Paveglio et al., 2015); residents' actions and adaptation (Brenkert-Smith, 2006); and community social diversity and vulnerability (Paveglio, Nielsen-Pincus, Abrams, & Moseley, 2017; Paveglio, Prato, Edgeley, & Nalle, 2016). However, work to assess wildfire risk by integrating social and natural systems is relatively new (Cutter, Boruff, & Shirley, 2003; Davies et al., 2018; Gaither, Goodrick, Murphy, & Poudyal, 2015; Gaither et al., 2011; Oliveira, Zêzere, Queirós, & Pereira, 2017; Parisien et al., 2016; Wigtil et al., 2016) or applied at limited geographic scales (Fischer, Kline, Ager, Charnley, & Olsen, 2014; Nielsen-Pincus et al., In review; Olsen, Kline, Ager, Olsen, & Short, 2017; Paveglio, Edgeley, & Stasiewicz, 2018; Paveglio et al., 2016), leaving a gap in our knowledge about large-scale transboundary risk in relation to behavioral response to fire. Our first goal is to understand where transboundary large fire events originate and how they spread through a mosaic of land tenures, management jurisdictions and fuel models, and quantify their impacts on the communities of three socially and biophysically distinct fire-prone regions of the western US.

In this study we used a methodological framework that accounts for the transmission of fire exposure among federal, state/local government, private lands and communities. A large percentage of fire events that affect developed areas in the western US originate on public wildlands (Ager et al., in review). Since socially vulnerable populations have relatively less capacity to absorb, recover and reduce risk and exposure from large wildfires (Cutter & Emrich, 2006; Davies et al., 2018), our second goal was to provide federal land managers with an assessment of the social conditions of the populations mostly affected (spatially defined as either communities or census block groups) by wildfires originating on adjacent public administered lands, to incorporate and adapt this knowledge in their management strategy.

Complementary to the two main goals, we produced results that can answer more detailed site-specific questions for each study area: (1) Which populated places are the most socially vulnerable and how do they vary in terms of social characteristics? (2) What are the amounts and sources of fire exposure for those places? (3) Do high social vulnerability populated places receive disproportionately higher amounts of fire exposure from federal land tenures compared to other land ownerships, and therefore, what are the implications in terms of federal responsibility for managing wildfire risk?

2. Literature review

We used the US Census Bureau for the American Community Survey (ACS) five-year estimates for the period 2011–2015 to select 21 social attributes (Table 1) to capture the level of resilience to wildfires at the scale of US block groups and communities (Cutter et al., 2003; Davies et al., 2018; Flanagan, Gregory, Hallisey, Heitgerd, & Lewis, 2011; Fothergill, 1996; Peacock, Morrow, & Gladwin, 1997; Wigtil et al., 2016; Wright, Rossi, Pereira, & Weber-Burdin, 2012). Social conditions, including wealth, poverty, race and age can often influence wildfire preparation and mitigation (Nielsen-Pincus, Ribe, & Johnson, 2015;Paveglio, Brenkert-Smith, Hall, & Smith, 2015; Paveglio et al., 2018; Wigtil et al., 2016). These social attributes are linked with social vulnerability to wildfires and describe a community's: capability to quickly react to and escape from an emergency (e.g., too young or too old, lack of vehicle, disability and single-parent households); ability to absorb losses and enhance resilience to hazard impacts (e.g., poverty, income and education); diversity (e.g., minority status, poor ability to speak English); housing status and affordability (e.g., multi-family residential units, manufactured homes, overcrowding in housing, and group quarters); and predominant occupations (natural resources, service, and government jobs, unemployment rates).

2.1. Capability to quickly react and escape from an emergency

When a wildfire spreads at a high rate, people can be surprised, panicked and confused, leaving them less time to prepare for either evacuating or staying to defend their property (mean US response time is 3.3 h) (Corotis & Hammel, 2010). The lack of a vehicle, and the ratio of households to driving exits confines the mobility of populations and the evacuation potential during an emergency (Cova, Theobald, Norman, & Siebeneck, 2013). The very young and very old are generally limited in resources and self-sufficiency, as well as in their movement out of harm's way (Cutter & Emrich, 2006). Elderly and people with disabilities may have mobility constraints or concerns, increasing the burden of care during a wildfire (Cutter et al., 2003). Further, the greater the proportion of elderly in a community, the higher the inability or the lower the willingness to comply with mandatory evacuation orders and the fewer economic resources are available for the cases of low social class pensioners (Cutter & Finch, 2009; Mayhorn, 2005; Ngo, 2001).

Densely populated places within an extended intermix WUI, but with lower structure density, likely expose more people and structures to wildfire (Syphard, Brennan, & Keeley, 2014). In addition, when more people live in an area with a small number of emergency traffic exits, evacuation in case of a wildfire is restricted (Cova et al., 2013), increasing the chances of entrapment on clogged highways (Mutch, Rogers, Stephens, & Gill, 2011). Late mandatory evacuation orders increase the chance for injuries or deaths, especially when a very large number of people is involved, as happened in the 2018 Mati fire in Greece (Goldammer et al., 2019). In several cases, higher numbers of structures indicate that there is higher risk of house-to-house fire transmission (Cova, 2005), especially in countries where structures are built with flammable material (USA, Australia, Chile, etc.), and increased suppression difficulty.

2.2. Ability to absorb losses and enhance resilience to hazard impacts

Natural disasters disproportionally impact the poor because of factors such as inadequate housing, social exclusion, a diminished ability to evacuate, lack of property insurance, and more acute emotional stress, often ignored during emergency response operations (Fothergill & Peek, 2004). High income enables communities to absorb and recover from losses more quickly due to insurance, social safety nets, and entitlement programs (higher adaptive capacity) (Cutter et al., 2003). Homeowners with insufficient income have potentially lower capacity to conduct wildfire hazard mitigation efforts (Brenkert-Smith, Champ, & Flores, 2012). On the other hand, Paveglio et al. (2018) found that higher income correlated with increased sensitivity and overall risk, and higher-value homes were at higher risk to wildfire exposure. Age is also an influencing factor that, along with financial ability, defines the willingness and ability of a community to accomplish wildfire mitigation actions (Olsen et al., 2017). The young and the elderly may lack the physical and/or economic resources required for resiliency (Morrow, 1999; Ngo, 2001). Lack of education is strongly correlated with

Table 1
Social attributes used for social vulnerability index estimation and mean values for Washington (WA), California (CA) and New Mexico (NM). Data source: American Community Survey, five-year estimates (2011–2015).

Social attribute	Abbreviation	Range	Transformation	All States	WA	CA	NM
				Mean			
Total population	Population	0–39,454	none	1613	1460	1655	1438
Total number of households	Households	0–6661	none	549	558	548	527
Total number of housing units	Houseunits	0–7665	none	601	615	596	628
Below poverty line (%)	Poverty	0–100	% of poverty determined population	15.8	13.4	16.0	21.0
Unemployed (%)	Unemployed	0–100	% of population > 16 yr. old	4.7	4.0	4.9	4.3
Household median income (thousand $)	Income	0–250	none	66.4	65.2	67.9	46.3
No high school diploma (%)	NoHschool	0–100	% of population > 25 yr. old	10.7	6.5	11.6	10.7
Aged 17 or younger (%)	Age17	0–65.8	% of total population	22.5	14.4	13.8	16.0
Aged 65 or older (%)	Age65	0–100	% of total population	14.0	21.8	22.6	22.9
Civilian with a disability, in poverty status, 20 to 64 years (%)	Disability	0–41.6	% of total non-institutionalized population	1.5	1.9	1.4	2.5
Single-parent households (%)	SingleParent	0–100	% of total number of households	9.7	8.4	9.9	10.9
Minority (%)	Minority	0–100	% of total population	33.3	21.1	36.3	26.8
Speak English “less than well” (%)	English	0–76.1	% of population > 5 yr. old	8.0	3.3	9.2	4.2
Number of multi-family residential units (%)	Multifamily	0–100	% of total housing units	26.1	22.4	27.6	13.7
Number of manufactured housing units (%)	Manufactured	0–100	% of total housing units	4.8	7.0	3.5	17.0
Overcrowding in housing (%)	Crowding	0–100	% of total housing units	7.1	2.8	8.2	3.2
Lack of vehicle (%)	Vehicle	0–100	% of total housing units	6.7	5.8	6.9	5.3
Group quarters (%)	GroupQ	0–100	% of total population	1.1	1.4	1.0	1.6
Natural resources jobs (%)	NatRes	0–49.9	% of civilian employed population	4.2	4.5	4.1	4.8
Service jobs (%)	Service	0–53.3	% of civilian employed population	8.3	8.2	8.3	8.8
Government jobs (%)	Government	0–68.9	% of civilian employed population	6.7	7.6	6.3	9.3

poverty, poor health, and inadequate housing (CDC, 2011) and can in specific cases, lead to poor risk perception (Baker et al., 2009), inability to participate in wildfire risk education efforts (Champ et al., 2013), and failure to comply with public regulations for fire prevention, and early warning response during an emergency (Cutter et al., 2003; White, 2000).

2.3. Diversity, housing status and affordability

Minority status and language barriers are correlated to lack of preparedness (Naim, 2008), risk perception and warning communication (Ojerio, Moseley, Lynn, & Bania, 2011), and response differences (Fothergill, Maestas, & Darlington, 1999; Sugerman et al., 2012) compared to the majority population in the US. Extreme events and disasters can affect people living in group quarters, multi-unit buildings, crowded apartments or mobile homes, with a higher likelihood of injury and property damage (Bolin, 1994; Cutter, Mitchell, & Scott, 2000).

2.4. Predominant occupations

Higher percentages of people in natural resources jobs (e.g. farming, fishing, forestry, construction, etc.) is correlated with higher suppression spending if the job engages in suppression work (a positive effect on people’s lives), but may be severely impacted if planned work in the forest is lost due to a wildfire (Cutter et al., 2003). Service job workers (e.g. housekeeping, childcare, food industry, law enforcement, etc.) may suffer after a wildfire, especially to the extent jobs are tourism dependent (smoke issues and landscape aesthetics decline), as tourism revenues and the need for services decline (Cutter et al., 2003). Migrant workers engaged in agriculture and low skilled service outdoor jobs may suffer more from smoke exposure. State and federal government jobs tend to offer higher income and more job security (Lewis & Frank, 2002), which can translate to higher duration of residence, and higher levels of housing ownership, creating stronger place-based bonds that can change attitudes towards fire mitigation. Lewis and Frank (2002) also showed that vulnerable to wildfires population groups such as women, minorities and veterans appeared more likely to choose public employment. Finally, a strong correlation exists between unemployment and poor health, with higher rates of hospitalizations, medication use, and health care visits (Jin, Shah, & Svoboda, 1995). In addition, unemployed populations have lower income, lack the resources to implement fire prevention and home protection measures, and are at greater risk of prolonged unemployment following a wildfire.

3. Methods

This study was replicated at three locations in the western US (North-central Washington; Central California; Northern New Mexico) that included large areas of federally administered lands (Fig. 1), and areas that have a high potential of fire transmission and exposure to neighboring communities based on evidence from recent studies (Ager et al., in review; Evers, Ager, Nielsen-Pincus, Palaiologou, & Bunzel, 2019; Scott et al., 2015; 2016; USDA Forest Service, 2018). In each study area, social vulnerability was related to wildfire exposure (expressed as the annual values of either structures affected or burned area), with exposure tied to the land tenure where it originated. We emphasized on wildfire exposure originating from the USDA Forest Service administered lands, since it is the largest federal land tenure in all three study areas and has the highest potential for wildfire risk mitigation projects (USDA Forest Service, 2018).

To quantify social vulnerability, we used social attributes from the American Community Survey to estimate a composite index at the scale of census block groups and related it to data generated through wildfire simulation models. Furthermore, we added another spatial level of detail by analyzing the characteristics and exposure profiles of communities with high social vulnerability, as estimated from the census block group analysis. This coupling enabled us to understand which land tenures exposed communities and census block groups of high social vulnerability to wildfire, and how specific social attributes were related to high fire exposure, rather than the in-situ hazards. Finally, for the most socially vulnerable communities we examined what are the population characteristics on each community that indicate a negative response to wildfires, in relation to estimated wildfire exposure.

3.1. Study areas

North-central Washington (WA) covers an area of 35,500 km^2 and

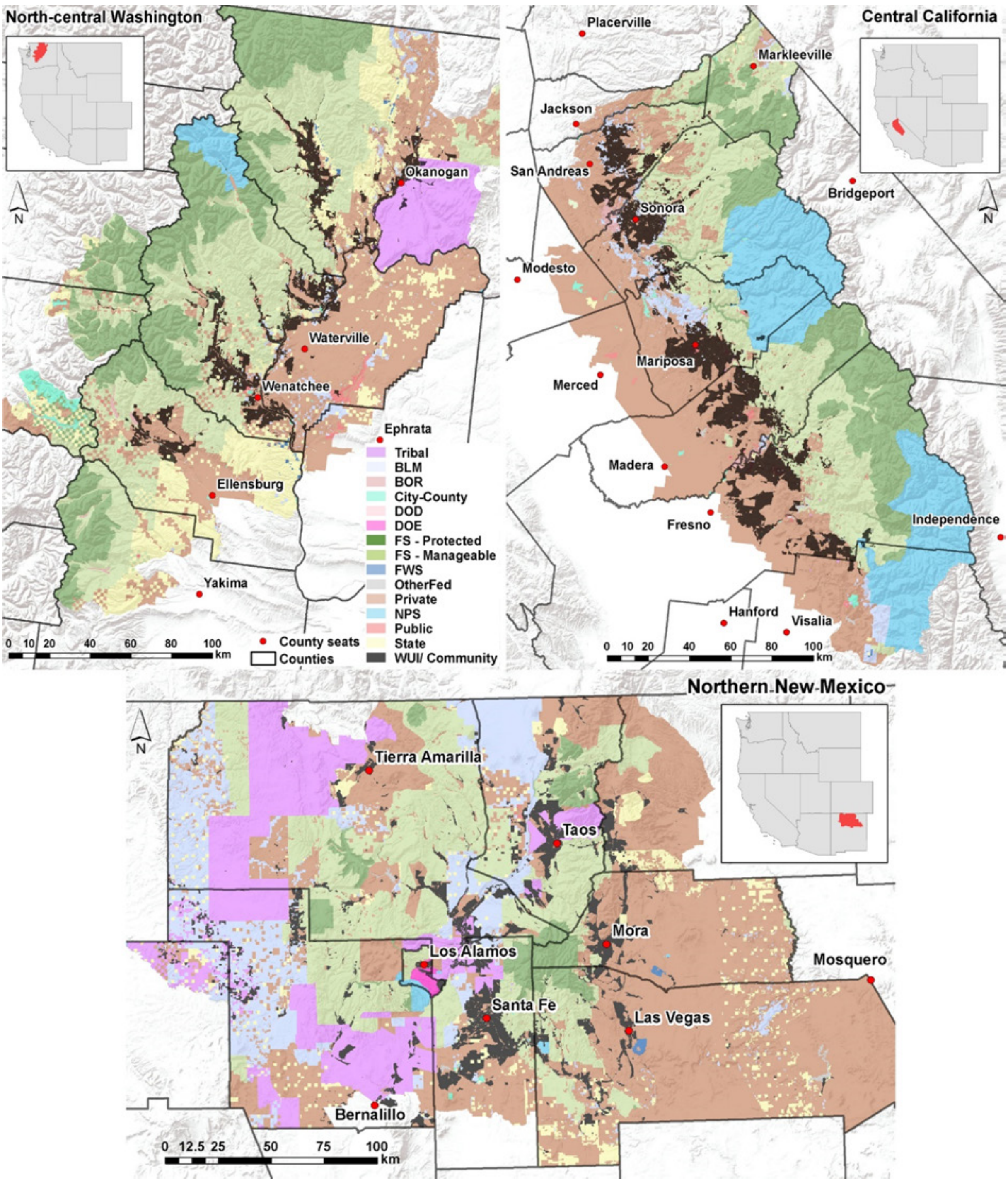


Fig. 1. Land tenures of North-central Washington (left), Central California (right) and North New Mexico (bottom). FS: Forest Service (M: Manageable; P: Protected); BLM: Bureau of Land Management; BOR: Bureau of Reclamation; DOE: Department of Energy; DOD: Department of Defense; FWS: Fish & Wildlife Service; OtherFed: Other Federal lands; NPS: National Park Service; Public: other public lands and non-government organizations.

contains most of the Okanogan-Wenatchee National Forest, and a large part of Mt. Baker-Snoqualmie National Forest. During 2009–2017, wildfires burned 12.1% of national forest lands in north-central WA, while 2.8% received mechanical treatments or prescribed fire. There are 64 communities completely or partially within the selected 151 block groups (BG) of north-central WA, with 199,000 people (5.6 people km^{-2}) in 74,250 households and 98,000 housing units (2.8 structures km^{-2}). The main land tenures within north-central WA are the US Forest Service (FS) (47.5% of the total study area), followed by private (21.5%), state (13%), tribal (4.7%) and Bureau of Land Management (BLM) or National Park Service (NPS) lands (3.5%). Wildland-urban interface (WUI – refer to Section 3.3. for details on how we defined WUI) covers 8.7% of the total area, comprised mostly of private (86%), state (6%) and FS (3.5%) administered lands.

Central California (CA) covers an area of 32,000 km^2 and completely contains the Stanislaus and Sierra National Forests, with smaller

Table 2
Social vulnerability index components, based on a principal component analysis with a varimax rotation, applied to the complete dataset of each US state.

Factor	Concept	WA	CA	NM	Dominant social attributes	WA	CA	NM
		Variance explained (%) (Eigenvalue)				Correlation		
1	Poverty	13.9 (4.29)	12.7 (1.95)	16.4 (4.64)	Poverty	+0.80	+0.73	+0.76
					Disability	+0.77	+0.76	+0.64
					Income	−0.75	−0.68	−0.74
					Vehicle	+0.52	+0.54	+0.70
					Unemployed	+0.50	+0.50	+0.43
2	Households and population	13.3 (2.45)	13.3 (2.83)	13.1 (2.84)	Households	+0.98	+0.98	+0.97
					Houseunits	+0.96	+0.97	+0.94
					Population	+0.90	+0.91	+0.92
3	Household composition	9.8 (1.68)	10.4 (1.50)	12.7 (2.21)	Age17	+0.81	+0.85	+0.85
					Age65	−0.72	−0.70	−0.78
					SingleParent	+0.62	+0.65	+0.73
					Crowding	+0.33	+0.36	+0.54
4	Education	13.7 (2.92)	16.6 (5.3)	9.2 (1.66)	English	+0.87	+0.89	+0.63
					NoHschool	+0.75	+0.85	+0.59
					Crowding	+0.64	+0.74	+0.08
					Minority	+0.59	+0.38	−0.39
					NatRes	+0.44	+0.52	+0.59
5	Housing type	9.4 (1.32)	8.0 (1.29)	8.0 (1.15)	Manufactured	−0.74	−0.65	+0.72
					Multifamily	+0.61	+0.63	−0.70
6	Occupation	5.6 (1.14)	5.4 (1.11)	5.4 (1.12)	Service	−0.62	−0.58	−0.32
					GroupQ	+0.57	+0.57	+0.93
					Government	−0.56	−0.54	−0.21
					NatRes	−0.14	−0.11	−0.21

parts of Humboldt-Toiyabe, Eldorado, Inyo and Sequoia National Forests. During 2009–2017, wildfires burned 14.5% of central CA national forests and 4.3% received mechanical treatments or prescribed fire. There are 124 communities completely or partially within the selected 344 BGs of central CA, with 530,000 people (16.6 people km^{-2}) in 175,000 households and 217,000 housing units (6.8 structures km^{-2}). The main land tenures within central CA are the FS, that administers 41% of the total study area, followed by private (25.6%), NPS (18%) and BLM (3%) lands. WUI covers 16.2% of the total area, comprised mostly of private lands (96%).

Northern New Mexico (NM) covers an area of 55,000 km^2. It contains the Carson and Santa Fe National Forests, and smaller parts of Cibola National Forest. During 2009–2017, wildfires burned 6% of northern NM national forests and 2.9% received mechanical treatments or prescribed fire. There are 134 communities completely or partially within the selected 211 BGs of northern NM, with 292,000 people (5.3 people km^{-2}) in 114,000 households and 148,500 housing units (2.7 structures km^{-2}). Most lands are private (41.5% of the study area), followed by FS (23%), tribal (12.7%), BLM (11.5%) and state (4.5%) lands. WUI covers 6.4% of the total area, comprised mostly of private (81%) and BLM (14%) lands.

3.2. Estimating social vulnerability

A Social Vulnerability Index (SOVI) was generated for all the blocks groups of each State using techniques detailed in other studies (Cutter et al., 2003; Tate, 2012) and described briefly below. From the 21 selected social attributes, 18 were transformed to percentages based on different population and household base metrics (see Table 1). The 21 social attributes were reduced to six principal components (Table 2). We used the “Psych” package (Revelle, 2018) in R 3.3.0 to run Principal Components Analysis (PCA) on a correlation matrix using the “Varimax” rotation method. The PCA was conducted using all attributes for the entire dataset of each state, thus SOVI is reflecting the relative social vulnerability of the larger population that resides in the more policy-relevant State administrative boundary. We removed those BGs with zero values on the total population or household attributes. Missing data were replaced by zero. We followed Cutter et al. (2003) and did not change the directionality of those attributes for which high values indicate lower levels of social vulnerability (Tate, 2012; Wigtil et al., 2016). Using the “nFactors” package in R (Raîche, Walls, Magis, Riopel, & Blais, 2013), we applied Parallel Analysis (Ledesma & Valero-Mora, 2007) to determine the number of factors to retain from the PCA.

Social Vulnerability Index scores were calculated for each BG by weighting each factor’s proportion of explained variance, and then summing the six weighted factors standardized using z-scores (Schmidtlein, Deutsch, Piegorsch, & Cutter, 2008). Finally, each BG score was categorized into low (values < -0.5), moderate (-0.5 to 0.5) and high (> 0.5) social vulnerability. Community social vulnerability was estimated by the percentage area within each social vulnerability class such that communities with: > 25% area in the high social vulnerability class were characterized as highly socially vulnerable; > 40% area in the moderate social vulnerability class, and not classified as highly socially vulnerable, were classified as moderately socially vulnerable; and all the remaining communities were classified as having low social vulnerability.

3.3. Estimating wildfire transmission and structure exposure

To calculate exposure to wildfire, we used wildfire fire perimeters and probabilistic hazard components generated from FSim across all three study areas (Finney, McHugh, Grenfell, Riley, & Short, 2011; Short, Finney, Scott, Gilbertson-Day, & Grenfell, 2016). FSim is often referred to as a “large fire simulator” because it models wildfire ignition and growth with the Minimum Travel Time (MTT) algorithm (Finney, 2002) focusing on relatively large and generally fast-moving fires. We used large fire simulations since they affect a larger spatial extent of fire hazard and the community’s response and planning. Spotting was

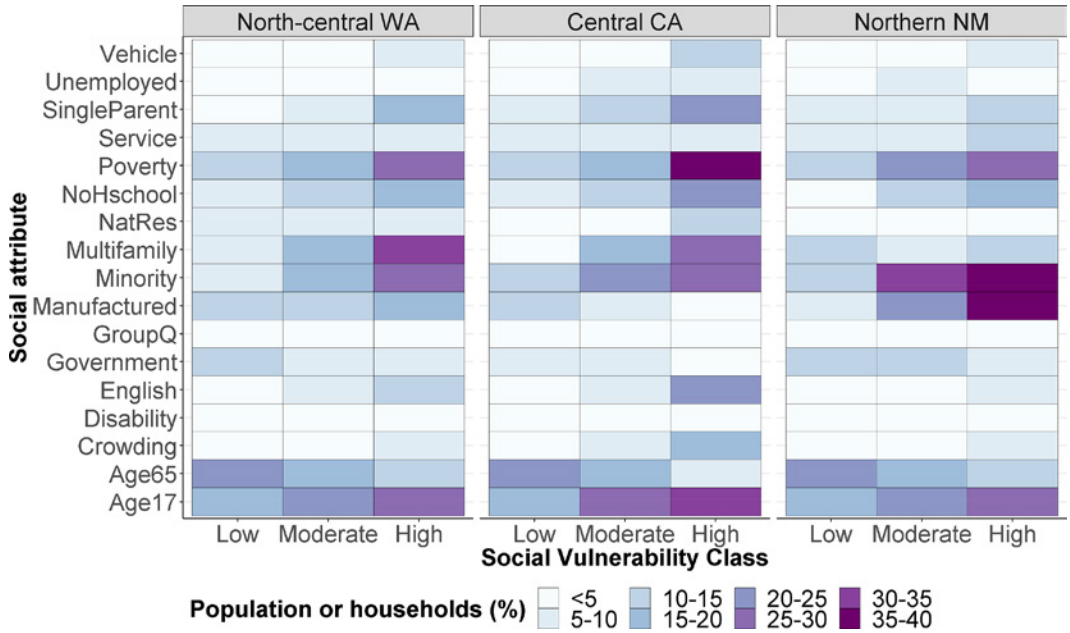


Fig. 2. Average percentage of population/households within each social vulnerability class by social attribute (see methods for vulnerability class and social attribute definitions). WA: Washington; CA: California; NM: New Mexico.

considered using the predictive model of Albini (1979). FSim incorporates modules for weather generation, wildfire occurrence, fire growth, and fire suppression, and is designed to simulate tens of thousands of hypothetical contemporary fire seasons (10,000 to 20,000 potential annual weather scenarios for the three study areas) (Finney et al., 2011; Short et al., 2016). Simulated perimeters were used to quantify the average annual area burned on each land tenure and the annual number of structures affected inside communities (Ager, Barros, & Day, 2015; Ager et al., 2014; Ager et al., 2017; Ager, Finney, & Vaillant, 2012; Ager, Palaiologou, Evers, Day, & Barros, 2018; Evers et al., 2019).

Community boundaries were comprised by SILVIS WUI polygons (Radeloff et al., 2005; SILVIS Lab, 2012) that intersect the USA Census Bureau populated places layer (defined as community "cores") (Census, 2016), and all other SILVIS WUI layer polygons (SILVIS Lab, 2012) that fall within a 45-minute drive time distance from the core (Appendix C). We removed polygons that had low structure density (< 2 housing units km^{-2}), since they were usually very large without the desired urban characteristics for this study. Each community could extend to more than one census block group, while each block group could contain tens of SILVIS WUI polygons, usually from more than one community. Community boundary data were combined with the land tenure layer derived from the Protected Areas Database (PAD) (USGS, 2016). We intersected the combined land tenure and community layer with the block group boundaries. The derived layer was then intersected with the FSim fire perimeter layer (Evers et al., 2019). Intersections provided the parts of each fire perimeter that enter or escape the boundaries of each community, land tenure and block group. Intersected parts were characterized as incoming (ignited on another community, land tenure and block group), self-burning (ignited inside the community, land tenure or block group boundary), or outgoing (the parts of the fire perimeter that escape the community, land tenure or block group boundary where the ignition occurred).

Then we summarized the annual number of structures exposed by each ignition for each WUI polygon. The total number of housing units (i.e. structures) within each WUI polygon was retrieved from the 2010 US census data (Census, 2016). By using the estimated burned percentage of each polygon, we calculated the percentage of affected structures from the total number, assuming equal spatial distribution of structures within each WUI polygon. For the same fire perimeter, we summarized the affected structures from all the affected WUI polygons (one-to-many), and for each individual community. To get annualized values for each ignition, we divided the sum of exposed structures (or hectares burned) with the number of fire seasons.

3.4. Community-based social vulnerability and exposure

We coupled the top-20 most exposed (based on standardized by community area structure exposure) high socially vulnerable communities with ACS community level social attributes to understand the characteristics of the exposed population. We kept the same variable transformations as we did during the block group SOVI estimation, except that we estimated income as the percentage difference from the maximum income of each study area so that all variables were expressed in percentages. Since north-central WA has only seven high socially vulnerable communities, we included the top-13 most exposed moderate social vulnerability communities in the assessment. We used a z-score standardized version of percentage social attributes to account for the different data ranges and derive meaningful comparisons among them (e.g. some variables had a range from 0 to 100%, while others from 0 to 45%).

All communities were grouped based on their social vulnerability classification (low, moderate, high) to visualize wildfire transmission as networks, with techniques adopted from social network analysis using the igraph 1.2.1 package in R (Csardi & Nepusz, 2006). We created a network for each study area where each rectangle represents the sum of fire received by all low, moderate or high socially vulnerable community groups, while edges and node size represent the amount of outgoing fire originated from each land tenure.

4. Results

4.1. Social vulnerability index

The six composite factors explained on average 65.5% of the total variation (Table 2). The factors with the highest explained variance were Poverty (northern NM and north-central WA) and Education (central CA), and the factor with the lowest explained variance was

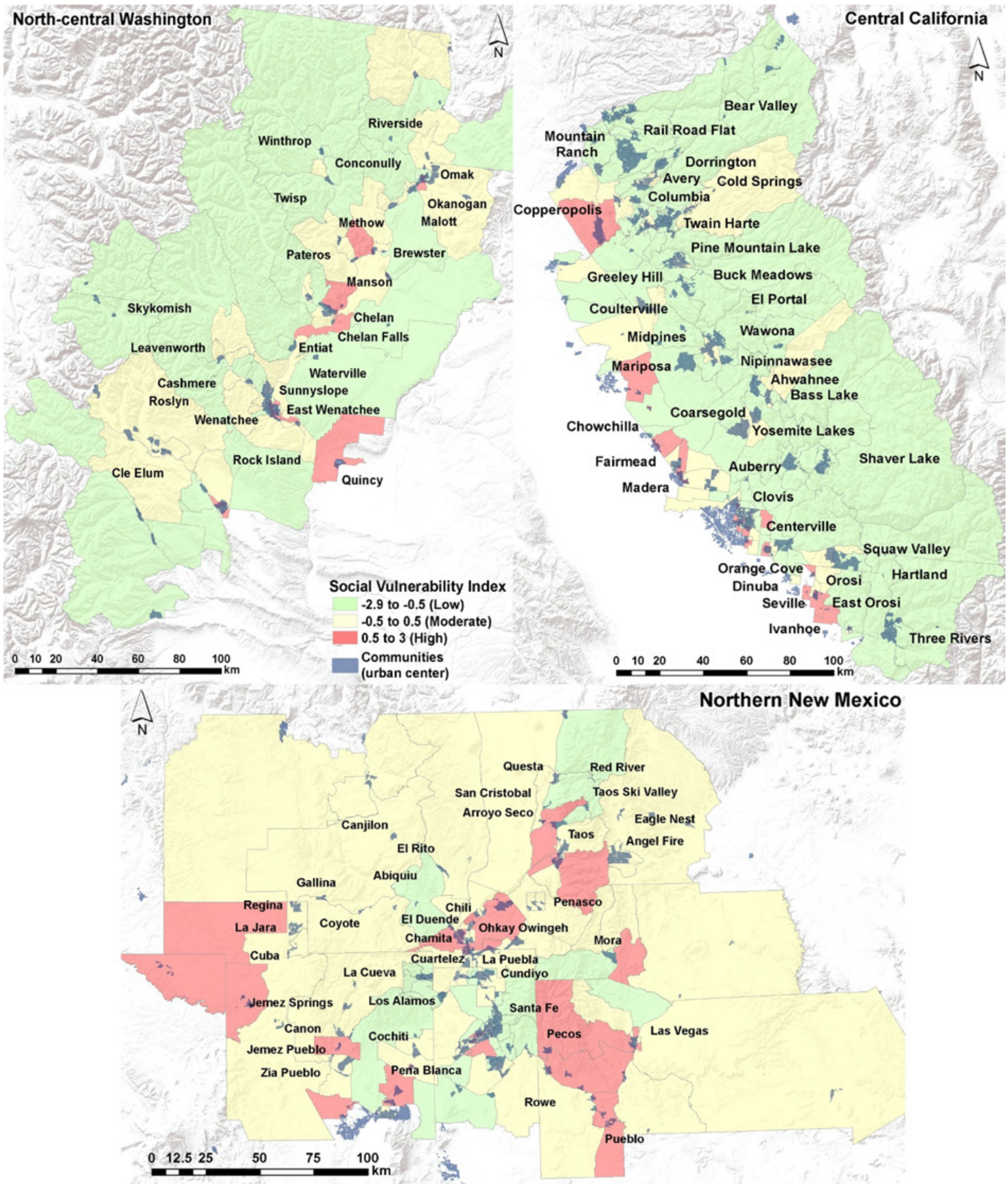


Fig. 3. Spatial distribution of social vulnerability index values for the US Census block groups for each study area.

Occupation for all study areas. An important common component for the three study areas was Households and Population (variance explained > 13%). Three attributes with negative correlations were common for all study areas (Income, Age65 and Government; see Table 1 for attribute abbreviations), while other attributes were negative for central CA (Manufactured and Service), north-central WA (Manufactured) and northern NM (Multifamily).

Some social attributes were correlated with overall social vulnerability (Fig. 2). In central CA for example, the social attributes of Minority, Multifamily, Poverty, Age17, English, Crowding, SingleParent and NoHschool were highly correlated with high social vulnerability based on the average percentage of population or households for each social vulnerability class. In northern NM, the social attributes of Minority, Poverty, Manufactured, Age17 and SingleParent were also correlated with high social vulnerability. Finally, high social vulnerability in north-central WA was correlated to Multifamily, Poverty, Minority, Age17, SingleParent and NoHschool. A few attributes were negatively correlated with social vulnerability, for example, Age65 for

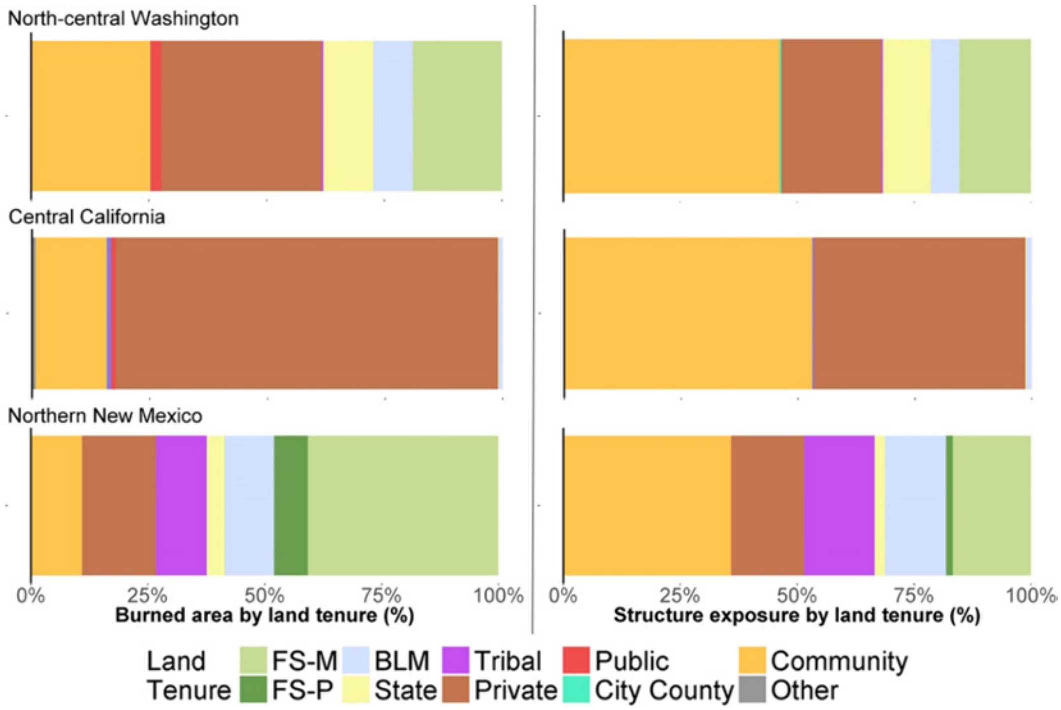


Fig. 4. Percentage area burned (left panels) and percentage structure exposure (right panels) by simulated wildfires ignited on neighboring land tenures for the high social vulnerability block groups for the three study areas by ignition source land tenure. FS: Forest Service (M: Manageable; P: Protected); BLM: Bureau of Land Management; Public: other public lands and non-government organizations.

all study areas, similar to the findings of Cutter et al. (2003). An explanation might be that higher percentages of elderly population reside in block groups with higher income.

4.2. Social vulnerability and sources of fire hazard to block groups

Most BGs in north-central WA were classified as low social vulnerability, with only 3% in high and 25% in moderate social vulnerability classes (Fig. 3). Central CA had less moderate (15%) but a similar percentage of high social vulnerability BGs (4%). Most BGs in northern NM had moderate social vulnerability values (76%), followed by high (13%) and low (11%).

Burned area by land tenure (Fig. 4, left panels), estimated for the highest social vulnerability block groups of each study area, was not directly related to structure exposure (right panels), since a block group can receive large amounts of simulated fire from a land tenure that did not burn inside urban areas. For example, fires ignited on private lands burned 80% of high social vulnerability block groups in Central CA but caused less than half of the total structure exposure in Northern NM; fires ignited on FS administered lands in Northern NM burned half of the total predicted burned area but caused less than 20% of the total structure exposure.

North-central WA had the highest total annual amount of estimated fire (32,000 ha yr^{-1}) for all block groups (sum of self-burning and incoming fire), with most burned area created from ignitions on FS (56%, i.e. the percentage of area burned within block groups from this fire source), private (17%), and state (13%) lands and communities (8%) (Appendix A: A). High social vulnerability BGs were mostly affected by fires that ignited on private lands (34%), within community WUI (25%) and on FS lands (19%) (Fig. 4, left panels). For central CA, the total annual estimated area burned was 18,000 ha yr^{-1} for all block groups, originating from private (48% of all burned lands), FS (23%), community (19%) and NPS (5%) lands (Appendix A: B). High social vulnerability BGs were substantially affected by private lands (81%) and communities (15%) (Fig. 4, left panels). Finally, Northern NM had the lowest amounts of total annual estimated area burned (14,000 ha yr^{-1}) for all block groups, with most burned area ignited on FS (41% of all burned lands), private (39.5%), tribal (7%) and community WUI (5%) lands (Appendix A: C). High social vulnerability BGs burned the most from FS (48%), private (16%) and community (11%) ignitions (Fig. 4, left panels).

The bulk of simulated structure exposure (> 85%) was caused by larger fires (> 1000 ha) with an average fire perimeter area of 11,540 ha in north-central WA, 6400 ha in central CA and 4650 ha in northern NM. Structure exposure caused by FS ignitions and the share of FS area in north-central WA were proportional (41.7% of all structure exposure vs. 47.5% of total area), similar to private (19% exposure vs. 21.5% area) and state lands (10% exposure vs. 13% area). WUI covered the 8.7% of the north-central WA and ignitions there created the 27% of the total structure exposure; on the contrary, tribal lands covered 4.7% of the study area but were the source of only 0.9% of total structure exposure. High social vulnerability block groups received 1.5 times the exposure than area would predict (4.4% of total exposure vs. 2.9% of area). The major structure exposure contributors in high social vulnerability BGs were WUI (46%) and private land (21%) ignitions (Fig. 4, right panels).

In central CA, FS administered lands created disproportionately lower structure exposure compared to their area (13% of exposure vs. 41% of area), while private and BLM lands were more balanced (27% and 3.1% exposure vs. 25.6% and 3% of area respectively). NPS lands (18% of central CA) created less than 1% of exposure; on the contrary, WUI ignitions created 55% of exposure (16.2% of central CA). High social vulnerability BGs received 1.25 times more exposure than area would be expected based on area (4.7% exposure vs. 3.8% area). The major structure exposure contributors in high social vulnerability BGs were communities (53%) and private lands (45%) (Fig. 4, right panels).

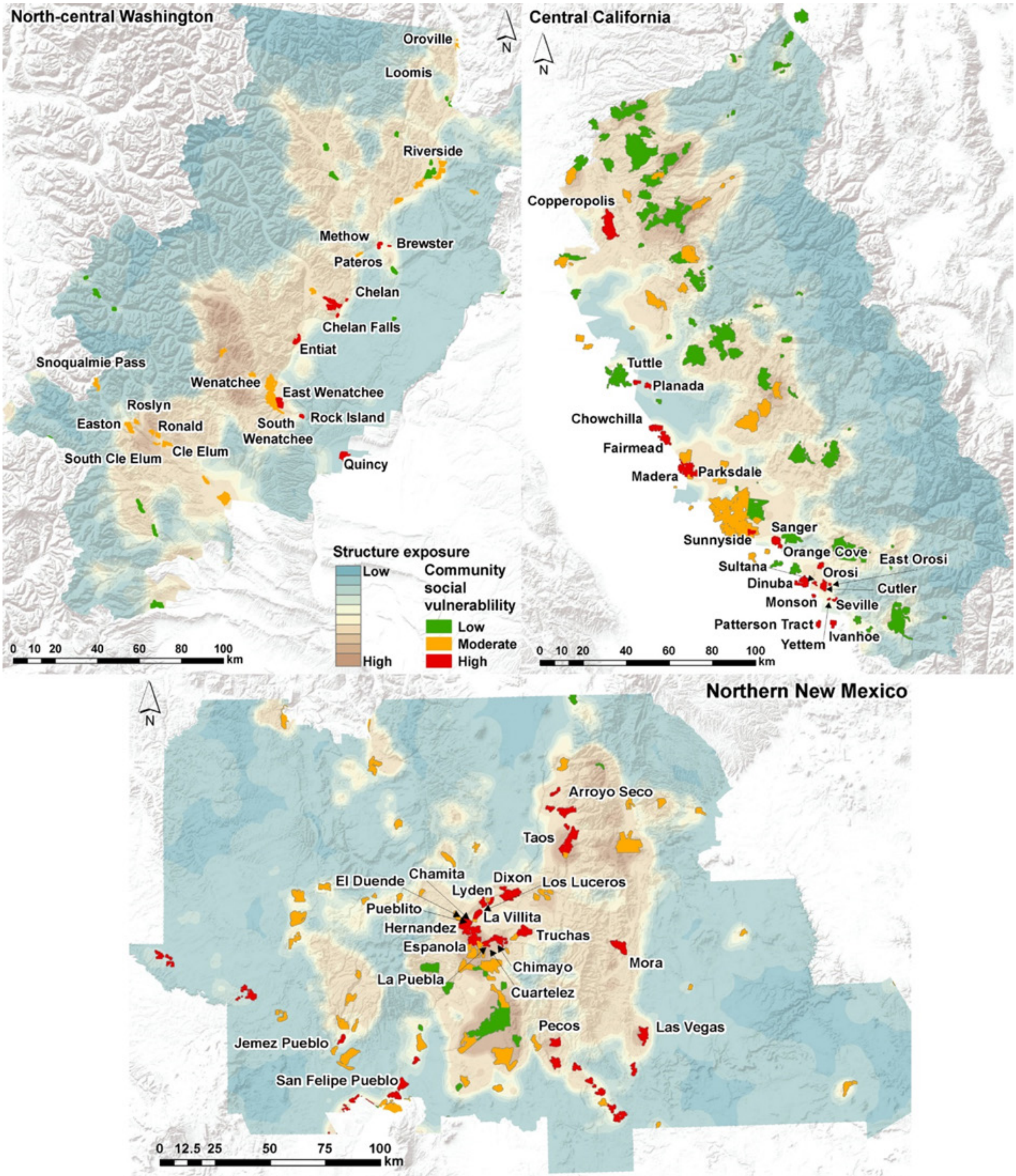


Fig. 5. Community firesheds and social vulnerability for each study area. Community names are shown for the high social vulnerability communities.

In northern NM, FS administered lands exposure was proportionate to its area (24.3% of exposure vs. 23% of area), similar to tribal lands (12.3% exposure vs. 12.7% area). Private, BLM, and state lands cover 41.5%, 11.5% and 4.5% of northern NM respectively, they caused only 15%, 7% and 2.5% of total exposure respectively. WUI ignitions caused 37% of all structure exposure, while covering the 6.4% of northern NM. High social vulnerability BGs received 1.5 times more exposure than area would predict (19.3% of total exposure vs. 13% area). For high social vulnerability BGs, the majority of exposure originated from ignitions on WUI (35.9%), FS (18%) and private lands (15.5%) (Fig. 4, right panels).

4.3. Social vulnerability and fire transmission to communities

We filtered transmission results to estimate the amount of transmitted fire and structure exposure from land tenures specifically to communities (only incoming fire, excluding self-burning from ignitions within the WUI polygons of the same community), in relation to their

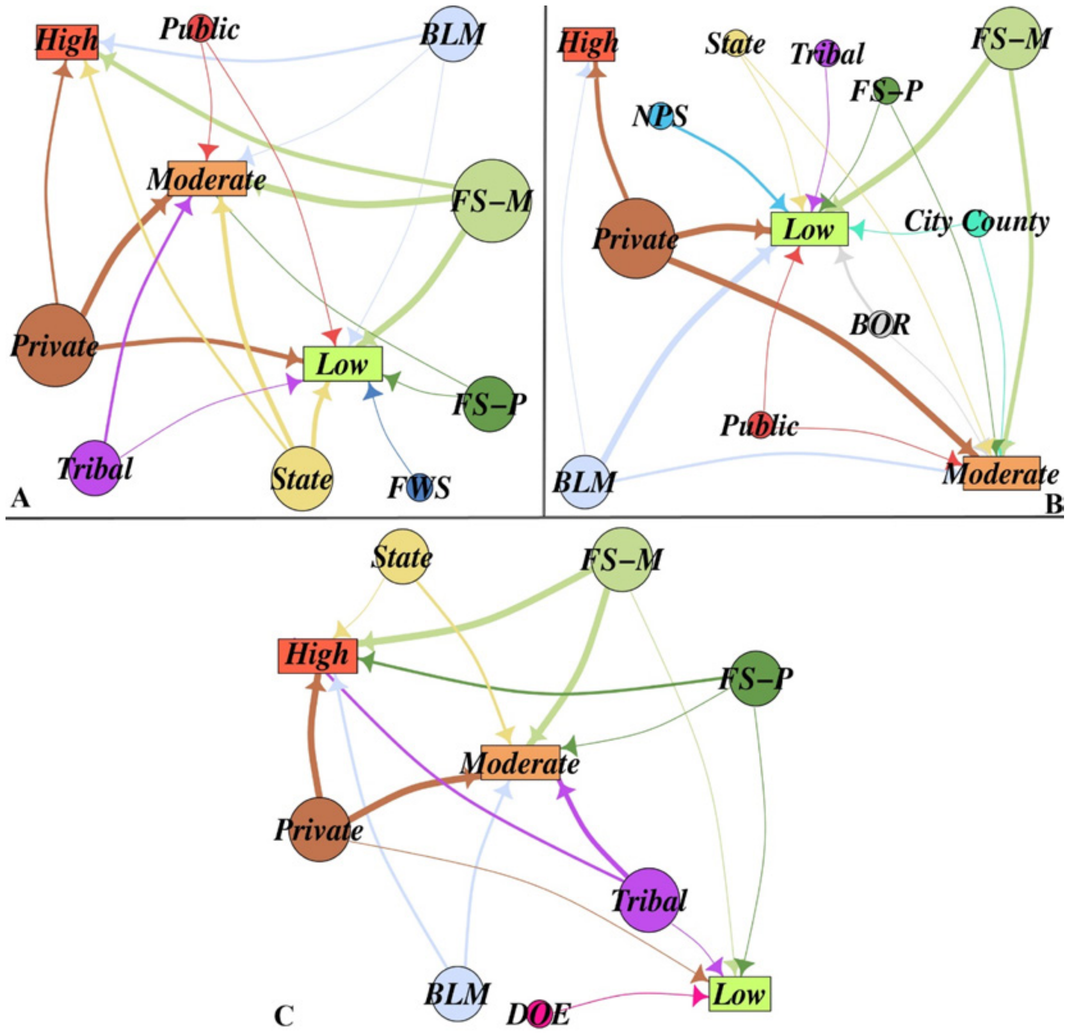


Fig. 6. Networks of fire transmission to communities based on their social vulnerability classification (low, moderate, high). A: North-central Washington; B: Central California; C: Northern New Mexico. Circular nodes represent transmitting land tenures, while node size is the amount of outgoing fire. Rectangular nodes represent communities in the different social vulnerability classes. Arrow width indicates outgoing area burned. FS: Forest Service (M: Manageable; P: Protected); BLM: Bureau of Land Management; NPS: National Park Service; FWS: Fish & Wildlife Service; BOR: Bureau of Reclamation; DOE: Department of Energy; Public: other public lands and non-government organizations.

social vulnerability characterization. Results differed from those of block groups (Fig. 4) since transmission estimates were performed at a finer scale (community cores and WUI).

All study areas had approximately 30% of their population residing in communities characterized as high socially vulnerable (Fig. 5). Most north-central WA communities were classified as low (n = 32), while 24 communities as moderate. Seven communities had high social vulnerability (Chelan, Chelan Falls, East Wenatchee, Quincy, Entiat, Brewster and Rock Island), receiving 11% of the total predicted exposure. There were 78 communities in central CA with low, and 27 with moderate social vulnerability. Of the 20 high social vulnerability communities, receiving 4.5% of the total predicted exposure, the seven most important in terms of structure exposure were Copperopolis, Madera, Orange Cove, Chowchilla, Fairmead, Orosi and Sultana. Most communities in northern NM were characterized as moderate (n = 75), with another 17 as low social vulnerability. There were 42 high social vulnerability communities that received 28.5% of the total predicted exposure, with the seven most important being Mora, Espanola, Las Vegas, Chimayo, Jemez Pueblo, La Puebla and Taos.

Fire transmission networks (Fig. 6) revealed the different fire transmission patterns from major land tenures to communities (low, moderate and high; rectangles), excluding community self-burning. High social vulnerability communities in north-central WA (Fig. 6-A) received fire from four land tenures (seven for moderate and eight for low). Only two land tenures transmitted fire to high social vulnerability communities in central CA (Fig. 6-B) (eight to moderate and nine to low social vulnerability communities), suggesting that the problem is less complex than elsewhere. Compared to the other two study areas, there was more diversity in land tenures transmitting wildfire to high social vulnerability communities in northern NM (six tenures) (Fig. 6-C). The majority of area burned transmitted to the north-central WA high social vulnerability communities came from ignitions on FS lands (40% of all transmitted fire), falling to 24% in northern NM and zero for central CA. These high social vulnerability communities were also affected by private lands and other communities (or self-burning) ignitions (47% in WA, 97% in CA and 62% in NM).

In Fig. 7 we present the most exposed high social vulnerability communities, ranked by standardized structure exposure, calculated by dividing the sum of annual structures exposed from each contributing land tenure with the total area of each community (ha). Most

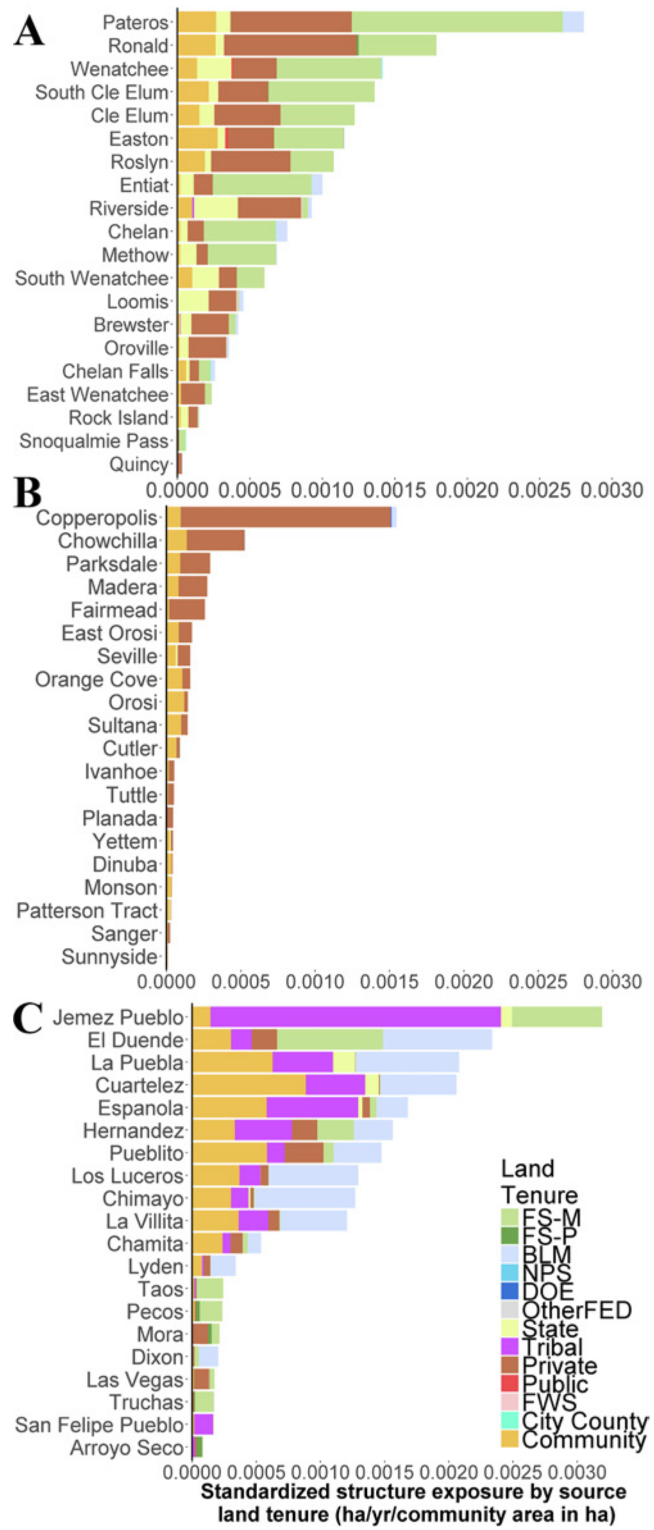


Fig. 7. The top high social vulnerability communities in terms of standardized structure exposure by source land tenure for A) North-central Washington; B) Central California; C) Northern New Mexico. Standardized values were calculated by dividing the sum of annual structures exposed by each contributing land tenure with the total area of each community (ha).

communities in north-central WA received high structure exposure from FS administered lands (e.g. Pateros, Entiat, South Cle Elum, Methow) (Fig. 7-A), with the remaining exposure been transmitted from other community WUI fires, private, state and BLM ignitions. For central CA, Copperopolis was the most exposed community, and there was strong fire transmission for all the high social vulnerability communities from private lands and other community WUI ignitions (Fig. 7-B). Socially vulnerable communities in northern NM also had high standardized structure exposure, mostly exposed from other community WUI fires, BLM, tribal and FS ignitions (Fig. 7-C), while seven communities received substantial structure exposure from FS administered lands (Jemez Pueblo, El Duende, Hernandez, Taos, Mora, Pecos, Truchas).

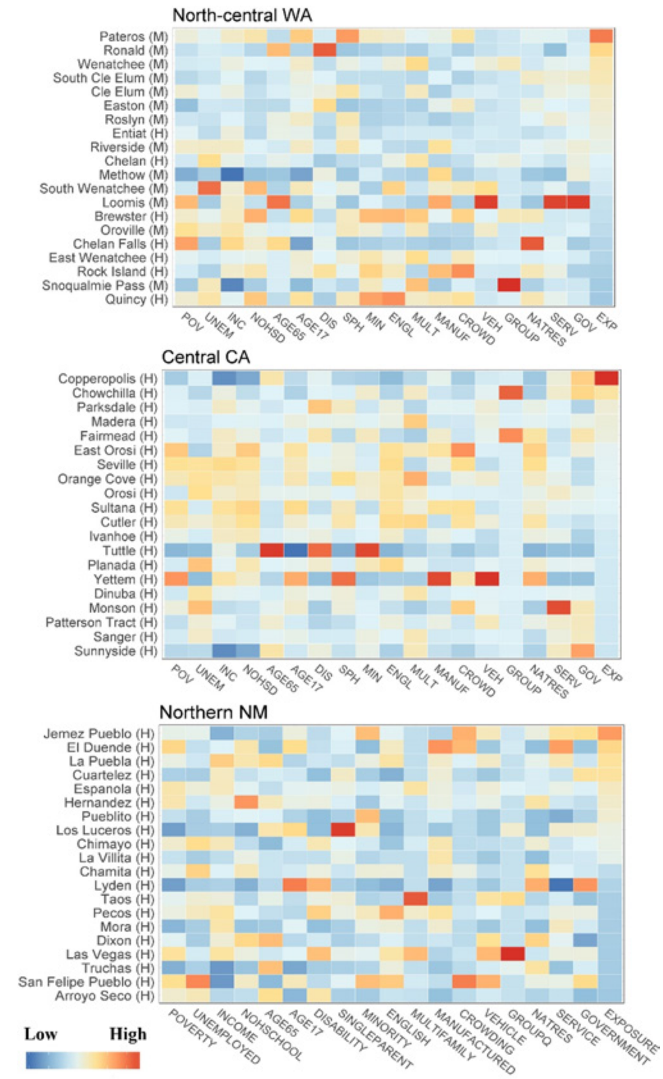


Fig. 8. The 20 most socially vulnerable communities and the average value of each social attribute for each study area. Communities were ranked from highest (top community) to lowest structure exposure, expressed as a percentage of the total study area exposure. Warmer colors indicate higher percentage of populations (or structures for exposure) with the characteristics of each variable. Letters in parenthesis denote the overall social vulnerability of each community (M: Moderate; H: High). See Table 1 for definitions of social attributes.

4.4. Linking community social vulnerability, structure exposure and social attributes

In Fig. 8, a heatmap of the 20 most exposed (i.e. standardized structure exposure) socially vulnerable communities within each study area (i.e. the same as those in Fig. 7) provides a detailed breakdown of each community's social attributes from a social vulnerability perspective, in relation to the predicted annual structure exposure, expressed as the percentage of the total exposure of each study area. As explained earlier, we added 13 moderate social vulnerability communities for north-central WA ("M" in parenthesis). The heatmap allows us to identify which communities have a specific social characteristic, e.g., for high percentages of elderly population, Loomis and Ronald (WA), Tuttle and Copperopolis (CA), and Truchas and Dixon (NM) stand out. Furthermore, we can identify which populations are expected to be more exposed for the higher ranked communities. For example, Chimayo (NM) had high unemployment and disability, Chelan Falls (WA) high poverty, lower income and high number of elderly populations, and Orange Cove (CA) high unemployment and poverty with low income. Complementary to the above results, in Appendix B we present the 20 most exposed communities only for fires ignited on FS administered lands.

5. Discussion

Wildfires do not affect all members of society equally yet, wildfire management has failed to integrate the social system into planning due to the lack of a widespread recognition of the connections between how fires affect people and the underlying causes of social vulnerability (Blaikie, Cannon, Davis, & Wisner, 2004; Fothergill & Peek, 2004). In this study we defined social vulnerability as "a person's or group's capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (Blaikie et al., 2004; Cutter & Finch, 2009), and we examined it in relation to the transboundary large-fire risk.

Larger uncontrolled fires expose more structures due to the difficulty of suppression on the periphery of each community and the conditions (i.e. increased intensity and spotting, fire-weather interactions and faster rate of spread) that large fires generate. We found that such fires (> 1000 ha) caused 85% of total structure exposure in northern NM and central CA, and 93% in north-central WA. In addition, communities are usually unprepared for large-fire events coming from many miles away, with Community Wildfire Protection Plans (CWPP) being spatially mismatched with the actual fireshed or extent of area where fires ignite and affect communities (Ager, Day, Short, & Evers, 2016). Larger fires, usually driven by extreme fire weather, are more likely to be transboundary events, which means that they can ignite many miles away from the affected community on a different land tenure. Smaller fires lack these transboundary characteristics, since they start and end on the same land tenure, and communities and fire suppression agencies may be more prepared to deal with local scale, frequent and less intense fires. Social vulnerability to large wildfires inherently includes this transboundary aspect that most of the previous studies did not address.

There were distinct geographic variations among the study areas in terms of land tenure composition and fire exposure. We found that national forests (i.e. FS administered lands) had a very strong exposure contribution in north-central WA and northern NM but caused only a fifth of the structure exposure problem in the highest social vulnerability block groups (Fig. 4). In contrast, national forests in central CA caused less than 13% of the total exposure, without affecting the high social vulnerability BGs. The bulk of structure exposure received from high social vulnerability BGs originated from the WUI and private lands, especially in central CA. Despite the relatively small amounts of fire exposure within these BGs, they can disproportionately affect people since one third of the population resides in high social vulnerability communities in each study area. At a community scale, ignitions on FS administered lands – or any other large land tenure – exposed a number of communities to the same fire, within large firesheds (sources) that potentially affect multiple communities (Fig. 5).

More than half of the estimated total structure exposure and area burned from ignitions on adjacent land tenures for all study areas and social vulnerability classes was predicted to originate from the WUI and private lands. Exposure from private lands, which includes forested areas located at the interface of federal wildlands and populated areas (Stein, Menakis, Carr, Comas, Stewart, Cleveland, Bramwell, & Radeloff, 2013), was proportional to their area for north-central WA and central CA. The majority of WUI is private and created disproportionately more exposure per area, since it covers a relatively small area, but with a high contribution to the total problem. WUI extends way beyond the strict boundaries of community cores, integrating large forested landscapes with flammable vegetation that are in proximity to larger federal land tenures. This finding can alter the perception of who is responsible for taking mitigation actions (e.g. landowner vs. local, state or federal agency) (Fischer et al., 2014), and suggests that homeowners, communities and private landowners should initiate shared-stewardship collaborations with larger land tenures and take actions towards reducing fire risk beyond the home ignition zone (HIZ) (Calkin, Cohen, Finney, & Thompson, 2014).

Structure loss in the WUI is not inevitable and actions to mitigate exposure can be achieved if communities start considering their biophysical sensitivity using the findings of this or previous research efforts to assess the probability and source of a potential wildfire event and the susceptibility of structures to wildfire (Calkin et al., 2014; Scott, Thompson, & Calkin, 2013). Targeted fuel treatments and fire exclusion zones located inside the WUI and close to the sources of fire hazard, while considering the major fire travel paths on the landscape (Finney et al., 2007), can have a substantial impact on reducing fire spread rates and intensity (but cannot stop or eliminate fires). Homeowners, and not public land managers, are responsible for reducing the probability of home exposure to flames and burning embers by considering housing design, construction materials and maintenance of a home's immediate surrounding (defensible space) (Cohen, 2000), actions which may be more challenging in high social vulnerability communities. Although communities can be categorized into different biophysical fire exposure (Evers et al., 2019) or social archetypes (Paveglio et al., 2015), each community is different and its social vulnerability, as examined in this research, can indicate where we expect higher adaptive capacity and where both landscape and HIZ mitigation measures should be subsidized or funded by the government.

Previous studies examined the relationship between perception, capacity and willingness of property owners to mitigate risk by treating hazardous fuels and reducing the susceptibility of dwellings/communities (Fischer et al., 2014; Nielsen-Pincus et al., In review; Olsen et al., 2017). Identifying locations where high wildfire hazard conditions coincide with limited mitigation activity among landowners can help to operationalize CWPP concepts and contribute to real reductions in the exposure of landowners, homeowners and communities to wildfire hazard (Ager et al., 2015); Fischer et al., 2014). Olsen et al. (2017) found that an increase in mitigation behavior inside homeowner properties alone would not be expected to make a sizable impact on reducing wildfire hazard over large landownerships, e.g. federal or state lands, since these properties comprise a comparatively small land area, and risk mitigation in the WUI must be applied on a broader spatial scale. Our results can be utilized by local officials to identify areas of both need and opportunity in terms of private landowner and homeowner cooperation with landscape-level mitigation efforts (Olsen et al., 2017).

Furthermore, our results suggested that even though national forests cover most of central CA and north-central WA study areas and were the second largest land tenure in northern NM, they generated proportionate per area structure exposure for north-central WA and northern NM, and disproportionately less for central CA, although the amount of structure exposure from national forests was still large in absolute numbers. One fifth of structure exposure in high social vulnerability census BGs in north-central WA originated on federal lands (FS and BLM), with higher levels found for northern NM (30%), and almost zero in central CA. Based on these findings, exposure was distributed among three key land tenures (WUI, private, federal/FS), with smaller contributions from tribal (in NM) and state lands (in WA and NM). These findings can better inform communities on their sources of fire risk and contribute towards reducing social conflicts concerning environmental issues and the management of federal lands (Carroll, Higgins, Cohn, & Burchfield, 2006).

This study did not seek to understand individuals', landowners' or communities' wildfire risk perceptions, an approach used in previous studies (Fischer et al., 2014; Nielsen-Pincus et al., 2015; Olsen et al., 2017; Paveglio et al., 2017). It rather implemented a broader spatial scale approach using the SOVI index, comprised of ACS block group attributes that are generally acknowledged to reflect social vulnerability to wildfires (Cutter et al., 2003; Smith, Keys, Lieske, & Smith, 2015; Wigtil et al., 2016). Using a single or just a few social vulnerability metrics can create discrepancies and can be misleading, e.g. a community with high economic capacity can have poor social structure (Corotis & Hammel, 2010), hence, a composite approach of the different social attributes was applied (i.e. Social Vulnerability Index). On the other hand, we could not neglect the importance of individual social components, since even a single component could tell much of the story of why a population within a block group or community has limited adaptive capacity and increased social vulnerability (e.g. high minority or elderly population percentage). Exposure-vulnerability heatmaps of individual social components allows to identify where specific cases of socially vulnerable populations are located on the landscape.

In addition, ACS metrics are useful for planning with limited research resources for broader spatial scales, since the cost of data acquisition and the time required for implementing a similar approach is minimized. The ACS metrics used here are not subjective (e.g. beliefs and perceptions) but are based on estimation and measurement of the actual on-site conditions, e.g. the number of elderly populations, average income, people in poverty etc. At the same time, a key disadvantage of the applied methods is that the use of ACS data removes the flexibility of adding specific and detailed questions to investigate measures such as adaptive capacity or informal social networks. In addition, the ACS data are survey data based upon a sample size much smaller than those in previous decennial censuses, thus if non-sampling and sampling error are not considered (margins of error or coefficients of variation) to assess the true value of the derived information (Wong, 2010), then uncertainty or error in spatial data should be expected when used in the real world (Openshaw, 1989). Another important aspect and consideration was the scale (Paveglio et al., 2018) of social data used (e.g. community vs. census block group), since it can produce different results when coupled with varying spatial scales of biophysical wildfire related characteristics (Oliveira et al., 2017; Wigtil et al., 2016).

There are few published applications of SOVI linked with wildfires (Gaither et al., 2015; Gaither et al., 2011; Poudyal, Johnson-Gaither, Goodrick, Bowker, & Gan, 2012; Wigtil et al., 2016), and SOVI has proved to be statistically robust and stable (Flanagan et al., 2011; Schmidtlein et al., 2008; Tate, 2012). The percentages of BGs with social vulnerability scores > 1.0 for our three study areas were close to each other ($\sim$12%), in agreement with similar studies which found 11% (Wigtil et al., 2016) and 12.5% (Cutter et al., 2003) of BGs, or counties of continental US respectively, with similar scores. In all study areas we found that the highest social vulnerability block groups had higher percentages of young people and minority members, with increasing levels of poverty and single parent households compared to the lower social vulnerability block groups, and a larger percentage of people residing in multi-family houses or manufactured homes (Fig. 2).

Wigtil et al. (2016) is an example of one of the few published fine scale approaches to assessing social vulnerability to wildfire, but did not account for the source of fire transmission to the block groups. Thus, their results lack a linkage to the fire source, which is crucial to mitigate transboundary fire transmission and the potential impacts from large fires. Without estimating and understanding the source of exposure to wildfires, as we did in this study, it is difficult to implement "all lands" risk management policies (USDA Forest Service, 2014), and the planning areas around communities will likely be on a spatial scale smaller than their exposure (Ager et al., 2015). Similarly, Oliveira et al. (2017) did not identified places on the landscape with large fire potential due to limited historical fire activity. Further, neither study provided detailed estimates of community level exposure. A key advantage of our approach is the ability to estimate wildfire exposure at various spatial scales, i.e. from the coarser scale of BGs (Fig. 4), to the finest scale of community (Fig. 7). Expanding our research to a larger scale (e.g., state, region or country level) can be achieved relatively easy with the use of a composite index like SOVI. Applying the SOVI approach at a community level, instead of block groups, is possible but requires more effort to retrieve and process the census data.

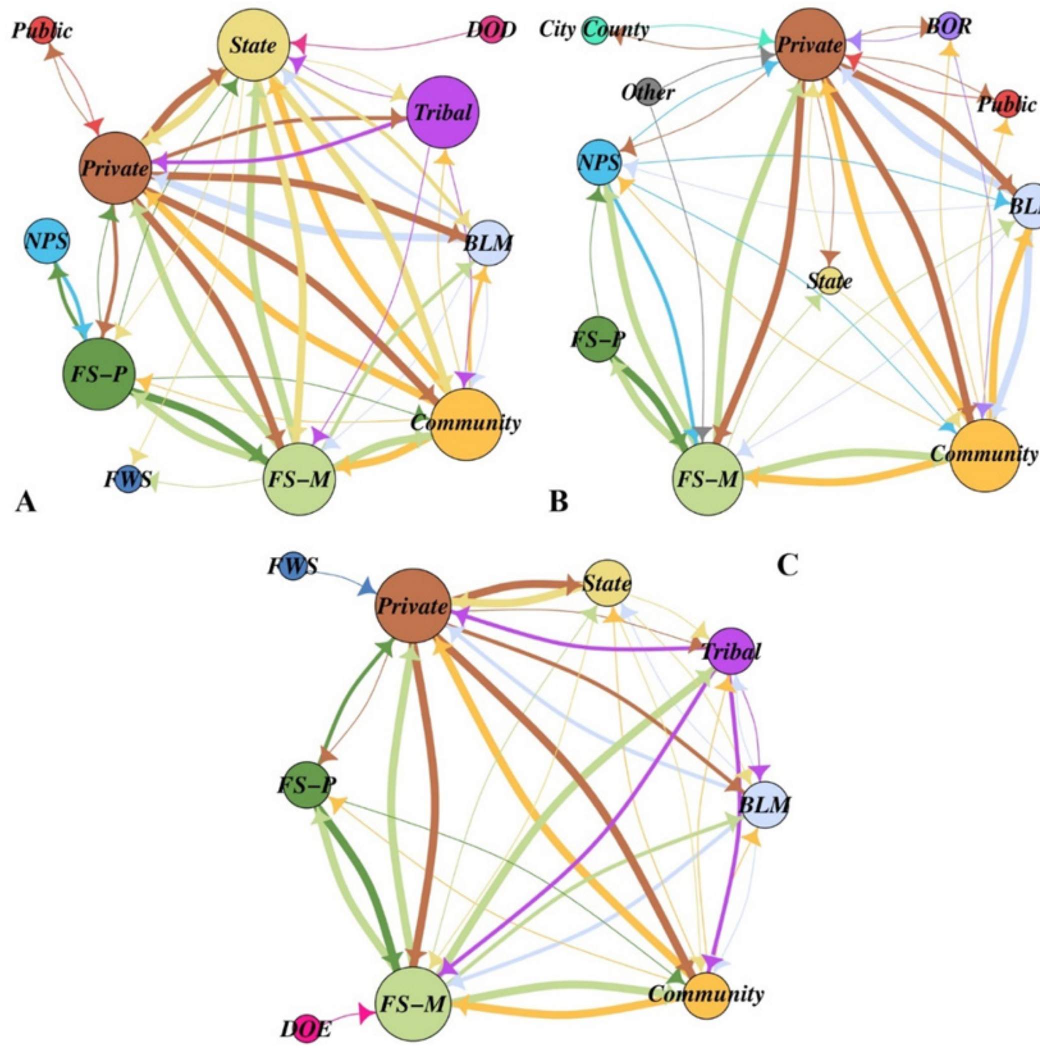
Our methodology was adapted and applied operationally by Headwaters Economics, in partnership with the City of Santa Fe Fire Department and the USDA FS Rocky Mountain Research Station, to produce a WebGIS tool that helped the city of Santa Fe in northern NM identify neighborhoods most at risk to wildfire, that were also identified as socially vulnerable populations (Headwaters Economics, 2017). The tool was designed to help city staff, residents, and land managers understand where the highest risk of wildfire overlaps with populations that may have social, economic, and health disadvantages to effectively and efficiently reduce risk. End-users found the tool and methods appropriate for education and outreach to those areas most at risk from wildfires and to the most socially vulnerable populations, as well as, to prioritize risk-reduction activities and mitigation funding based on specific socially vulnerable population characteristics.

6. Conclusions

Estimated wildfire hazard and transmission coupled with social data can help inform fuel management project planning and identify major stakeholders and vulnerable populations. Results can support large land tenures' assessment of which communities can be affected by potential ignitions on their lands, and if those communities can couple their risk mitigation planning and actions with those of the source side, assuming that high social vulnerability communities have limited mitigation capacity. Recognizing the sources of wildfire hazard to vulnerable communities at a landscape level can inform future urban planning to avoid expansion on fire-prone landscapes, especially in places where the composition and structure of fuels or/and landscape fragmentation among multiple land tenures do not allow effective fire risk mitigation. Socially vulnerable communities with high fire exposure can use our findings to ensure that their evacuation plans are up-to-date and there are sufficient escape routes to avoid disasters similar to the 2018 fire events of Paradise, CA and Mati, Greece, where the most vulnerable people could not move out of harm's way and were trapped inside the urban fabric. Finally, identifying multiple adjacent communities that are affected by the same fireshed and/or land tenure can provide economies of scale and in turn, facilitate communities' participation in risk mitigation shared-stewardship projects or allow communities to benefit from the positive outcomes of large-scale projects on public landscapes

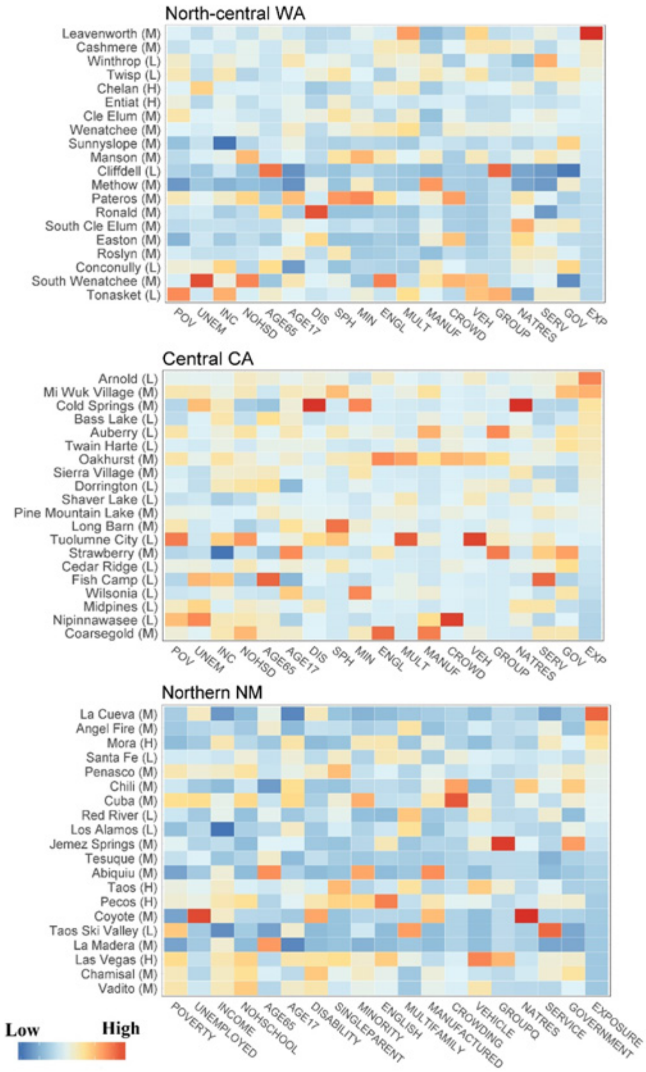
Appendix A

Fire transmission networks among the land tenures of each study area. A: North-central WA; B: Central CA; C: Northern NM. Node size is the sum of incoming and self-burn fire, while arrow size represents the amount of incoming fire received by each land tenure in ha yr^{-1}. FS: Forest Service (M: Manageable; P: Protected); BLM: Bureau of Land Management; NPS: National Park Service; FWS: Fish & Wildlife Service; BOR: Bureau of Reclamation; DOD: Department of Defense; Public: other public lands and non-government organizations.



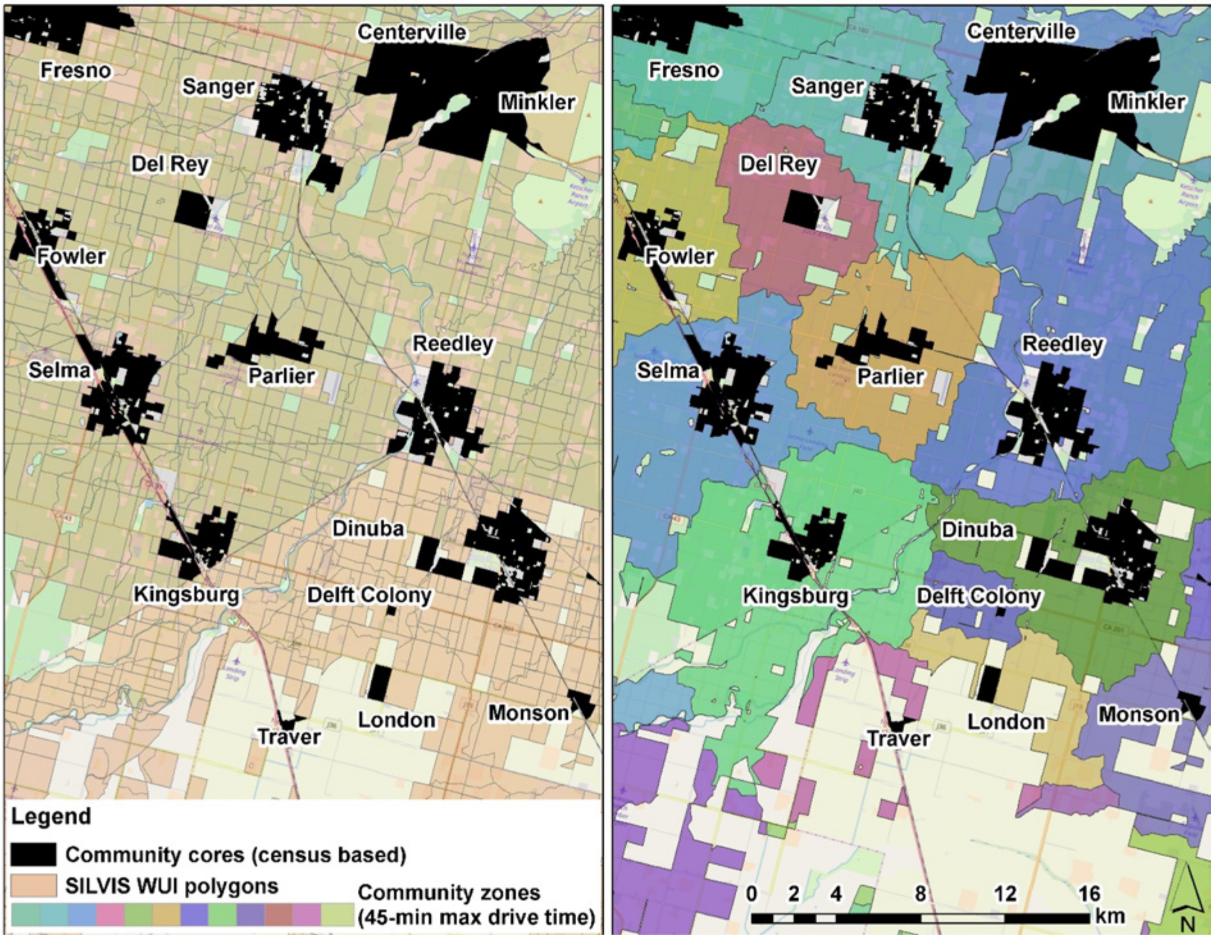
Appendix B

The 20 most exposed communities from fires ignited inside US Forest Service administered lands and their social attributes, scaled around the average values of each variable for each study area. Warmer colors indicate higher percentage of populations (or structures for exposure) with the characteristics of each variable. Letters in parenthesis denote the overall social vulnerability of each community (L: Low; M: Moderate; H: High).



Appendix C

Grouping of SILVIS WUI polygons around community cores, using a 45-minute drivetime from each core and the cost allocation model of ArcGIS. Polygons that are within a 45-minute drive time to multiple communities are assigned to the community with the shortest drive time from that location. Not all community boundaries go out to a 45-minute drive time, and they don't have the same area. A large drive time was set to minimize the number of SILVIS WUI polygons that were not assigned to any community.



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