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Socially vulnerable US Pacific Northwest communities are more likely to experience wildfires

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Abstract

Quantitative wildfire risk assessments increasingly are used to prioritize areas for investments in wildfire risk mitigation actions. However, current assessments of wildfire risk derived from fire models built primarily on biophysical data do not account for socioeconomic contexts that influence community vulnerability to wildfire. Research indicates that despite accounting for only a small proportion of high wildfire hazard areas, communities with fewer socioeconomic resources to devote to wildfire prevention and response may experience outsized exposure and impacts. We examined the distribution of simulated wildfire risk versus observed wildfire experience relative to social vulnerability across communities in the Pacific Northwest region of the United States. Using three decades of wildfire occurrence data, we investigated whether socially vulnerable communities were more likely to experience ignitions, fires that escaped initial attack (hereafter 'escaped fires') (>121 hectares), and large fires (>404 hectares), reasoning that each may reveal key insights into the effectiveness of current wildfire risk mitigation and response efforts. We found that communities located in areas with higher wildfire risk or hazard tended to have *lower* social vulnerability, but that across landscapes east of the Cascade Range, communities with *higher* social vulnerability were more likely to be exposed to ignitions, escaped fires, and large fires. Our results draw into question whether the current reliance on biophysical data in wildfire risk assessments, absent consideration of community socioeconomic conditions, may perpetuate social inequities by leading to over-investment in well-resourced communities and under-investment in socially vulnerable communities subject to disproportionate wildfire exposure.

1. Introduction

A combination of factors is increasing transmission of wildfires into communities, leading to a resurgence of fires that threaten human lives, livelihood, and property [1, 2]. Housing developments continue to expand the wildland–urban interface [3–5], exposing communities to the consequences of historical forest and fire management that is exacerbated by climate change [6–10]. Concurrently, climate change is increasing vegetation stress and combustibility within existing built environments [11], contributing to fire occurrence and transmission [12]. Wildfires can expose communities to adverse health effects from frequent and prolonged smoke exposure [13–16], damage to homes and critical infrastructure [17–21], and long-term economic and environmental impacts such as reduced water quality and declining property values [22–26]. In response to wildfire's growing social and economic impacts, many policymakers have sought greater investments in actions to reduce wildfire risk [27, 28]. Ensuring that these investments are appropriately targeted is essential to attaining the greatest return in terms of increased community resilience.

Efficiently allocating finite investments in wildfire resources often relies on quantitative wildfire risk assessments (QWRAs) that integrate measures of

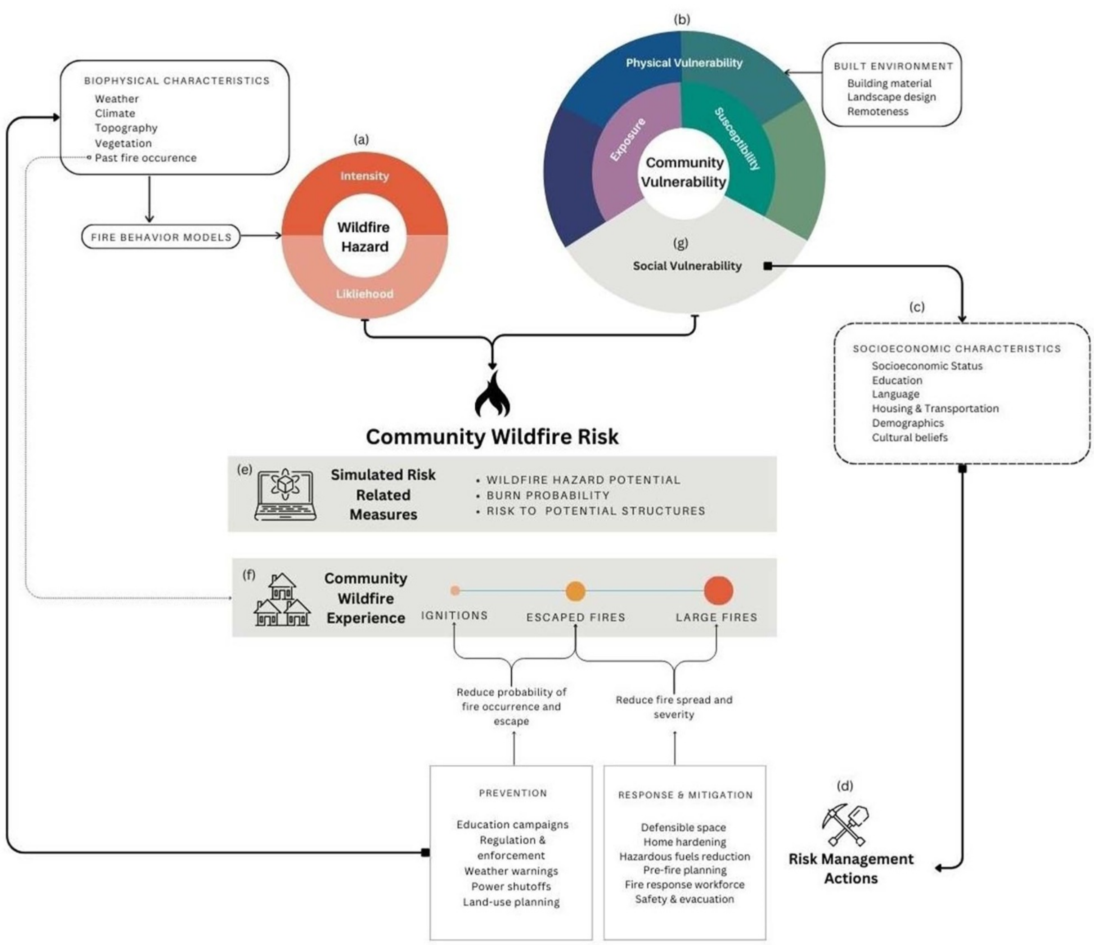

Figure 1. Diagram illustrating feedback between biophysical and social systems that influence wildfire risk and the how components of these systems are considered in quantitative wildfire risk assessments (QWRAs). (a) Wildfire hazard is shaped by biophysical characteristics of the landscape that result from ecological and human processes and (b) community vulnerability is shaped by the built environment and (c) socioeconomic characteristics which result from social systems. Human actors make decisions about (d) risk management actions that are informed by risk perceptions and influenced by socioeconomic contexts which alter the biophysical characteristics of the landscape and influence wildfire hazard. Current approaches to quantitatively assessing community wildfire risk involve estimating wildfire *likelihood* (or burn probability), the annual likelihood that a specific location will experience wildfire; and wildfire *intensity*, the amount of potential energy produced by a fire, should it occur. These rely on models that simulate fires based on biophysical data and past fire occurrences. Measures of wildfire hazard are then integrated with information on community vulnerability, typically the combination of *exposure* to wildfire (places where burn probabilities are nonzero) and the *susceptibility* of the community to negative fire impacts. Because community susceptibility is approximated with characteristics of the built environment, we refer to the combination of exposure and susceptibility as *physical vulnerability*. (g) Social vulnerability is sometimes thought of as the complement to physical vulnerability as it refers to pre-existing social and economic factors (e.g., access to financial resources, education, and evacuation capability, among others) that can influence overall vulnerability. While it is not routinely integrated into measures of wildfire risk, it can be mapped independently and used in conjunction with hazard and risk maps (indicated by the dashed border). Socioeconomic characteristics of communities can confer or limit access to fire risk management resources and actions, that in turn influence community wildfire risk and experience. Measures of burn probability, wildfire hazard potential, and risk to potential structures are collectively referred to as (e) *simulated risk related measures* to indicate that they are estimates derived from fire models. Where past fires occurrences intersect with communities is referred to as (f) *community wildfire experience* to clearly differentiate it from simulated measures of risk. Community wildfire experience is multidimensional, ranging from ignition to large fires, and wildfire experience is influenced by wildfire prevention actions and response capacity.

wildfire *likelihood* and *intensity* (collectively referred to as *hazard*) with measures of *vulnerability* (figure 1). Wildfire likelihood and intensity are typically estimated as weighted averages from Monte Carlo simulations using fire models that simulate thousands of hypothetical fire seasons based on landscape conditions, weather, topography, fuel type, and past fire occurrence [29]. When estimating wildfire risk to communities specifically, hazard data is integrated with measures of *community vulnerability*, defined as the *susceptibility* of resources to harm from *exposure* to a hazard [30]. Measures of community susceptibility are focused entirely on the built environment, assuming structure damage and losses are proportional to fire intensity [29]. While these assumptions may capture general trends associated with defensible space and building materials [31, 32], they disregard the socioeconomic conditions that can influence the vulnerability of individuals and communities to wildfire.

Community vulnerability to wildfire is not solely a function of the biophysical and built environment, but also of socioeconomic factors that can influence susceptibility—often referred to as *social vulnerability* [33]. Currently QWRAs do not integrate information on community social conditions, potentially obscuring our understanding of community wildfire risk. Another limitation of wildfire risk measures derived from complex modeling is that they do not aid in identifying potential leverage points for investments in fire mitigation and management associated with fire occurrence and development, especially as they relate to community socioeconomic conditions. While destruction of human structures is primarily driven by unplanned human ignitions that occur on private lands [12, 19], ignitions in wildlands that escape initial attack efforts often cross jurisdictional or ownership boundaries exposing nearby communities [12, 34]. Large transboundary wildfires in the west have been shown to disproportionately expose more socially vulnerable communities with limited capacity to mitigate fire risk and impacts [35]. Investigating fire ignitions, fires that escape initial attack and large fires, key stages in wildfire management, can further our understanding of the extent to which community socioeconomic status influences different dimensions of wildfire risk and inform more strategic investments in mitigation actions.

Prior research indicates that both wildfire risk and impacts can be moderated by the availability of social and economic resources (e.g. capacity to understand and complete evacuation orders, participation in pre-wildfire planning and available tax base to fund fire response units, among others) [18, 21]. Areas across the United States (US) with *higher* wildfire hazard potential (WHP) [36] are generally inhabited by wealthier, more well-resourced communities with *lower* social vulnerability [24, 35, 37–39]. Although wildfire *hazard* potential (WHP) falls primarily on wealthier communities with lower social vulnerability, in California, communities with lower incomes and property values experience more wildfires [38] and communities with higher proportions of older and low-income residents, higher unemployment, and lower home values, were associated with greater wildfire impacts [40]. Historically marginalized populations also face barriers that leave them less likely to participate in federal wildfire prevention programs [41]. Despite these observations, community social vulnerability has not routinely been considered in planning wildfire risk mitigation projects [42], and evidence suggests federal land management agencies have a higher probability of locating fuels reduction projects near communities that have experienced a nearby wildfire, and that the effect predominates among communities with higher socioeconomic status [43]. More generally, emergency managers are not well versed in the use of social vulnerability analyses, further limiting consideration of community socioeconomic status in hazard planning, mitigation and management [44].

In this study, we examine the relationships between community social vulnerability, wildfire risk, and wildfire experience for communities across the Pacific Northwest region of the US. From prior research, we hypothesized that communities affected by wildfires may differ from communities that have high measures of hazard or risk due to socioeconomic factors that are not accounted for within fire models and quantitative risk assessments. We sought to examine the implications of using current measures of hazard or risk, in the absence of socioeconomic information about communities, to guide wildfire resource allocation decisions and identify locations for targeted investments in fire prevention and response:

(1) What is the relationship between community social vulnerability and *simulated wildfire risk related measures* derived from fire models as compared to actual *observed community wildfire experience*?
(2) What is the relationship between community social vulnerability and community exposure to ignitions, escaped fires, and large fires?

2. Methods

2.1. Study area and community boundaries

We focused our analysis on communities in Oregon and Washington, two western states facing increased wildfire activity in recent years [45]. We used communities as our unit of analysis, instead of, say, number of individuals exposed (e.g. Modaresi Rad *et al* 2023) [46] because it enabled us to focus on the implications that likely wildfire exposure can have in terms of community-level capacity to address wildfire risk and recovery. We used the US Census Bureau's 2020 Census Designated Places (CDPs) with a 10 km buffer to represent communities and their area of potential wildfire experience. CDPs represent settled population centers defined by distinct residential cores and relatively high population densities with a degree of local identity [47]. Although a 10 km buffer zone may include ignitions and wildfires happening outside a community's official political borders, we theorized that if these events occur nearby, they may still cause worry among community leaders and residents about the risk of the fire spreading. This concern could prompt communities to implement monitoring efforts, and possibly even take steps to control and suppress the fire, aiming to prevent its further expansion and protect the community.

Table 1. Descriptions of simulated wildfire risk related measures and observed community wildfire experience measures.

Variable	Description	Source
Simulated wildfire risk related measures		
Wildfire hazard potential (WHP)	An index that quantifies the relative potential for wildfire that may be difficult to control and is often used to help prioritize where fuel treatments may be needed. WHP was developed using a custom Pyrologix utility called WildEST for the Pacific Northwest Quantitative Wildfire Risk. Data were developed specifically for the Pacific Northwest planning region in 2021.	[36, 53]
Burn probability (BP)	The annual probability of wildfire burning in a specific location. Data were developed specifically for the Pacific Northwest planning region in 2021.	[54]
Risk to potential structures (RPSs)	The expected risk to potential structures (RPSs) dataset represents a measure that integrates wildfire likelihood and intensity with generalized consequences to a home on every pixel. RPS is calculated by multiplying conditional risk to potential structures (cRPSs) and burn probability (BP). Data were developed specifically for the Pacific Northwest planning region in 2021.	[55]
Observed wildlife experience measures		
Ignitions	Count of ignitions (human and natural) between 0.04 and 121 hectares in size between 1992 and 2020 recorded in the USFS Fire Program Analysis Fire Occurrence Database.	[49]
Escaped fires	Count of fires (human and natural) that grew to 121 hectares acres or larger between 1992 and 2020 recorded in the USFS Fire Program Analysis Fire Occurrence Database.	[49]
Large fires	Count of fires (human and natural) that grew to a size larger than 404 hectares between 1984 and 2021 recorded in the Monitoring Trends in Burn Severity (MTBS) database.	[50]

Using buffered CDPs also allowed us to minimize over or under-estimation of community wildfire exposure that would have resulted from using contiguous geographic units that vary in size based on population, such as US Census tracts or block groups (see supplementary materials for a more thorough discussion of this issue).

Community boundaries were allowed to overlap, capturing wildfire events that simultaneously exposed multiple communities. Communities were designated as belonging to one of three distinct regions corresponding to major historical wildfire patterns for all analysis [48]: (1) CDPs on the eastside of the Cascade mountain range (hereafter 'eastside'), (2) CDPs on the westside of the Cascade range ('westside'), and (3) CDPs within the Environmental Protection Agency's level three Klamath Mountains ecoregion in Southwest Oregon ('Klamath').

2.2. Data acquisition

2.2.1. Community wildfire hazard, risk, and experience

We summarized three measures of wildfire hazard or risk derived from fire models which we refer to as *simulated wildfire risk related measures* for each CDP with a 10 km buffer (hereafter 'community'): (1) burn probability (BP), WHP, and risk to potential structures (RPSs). Each of these measures is used to support fire operations and inform prioritization of landscapes and communities for wildfire risk mitigation funding (e.g. The USDA's Community Wildfire Defense Grant Program). Simulated wildfire risk related measures were developed specifically for the Pacific Northwest planning region in 2021 and are defined in table 1. We also summarized three measures of *community wildfire experience*: ignitions, escaped fires (>121 hectares), and large fires (>404 hectares), each of which represent key stages

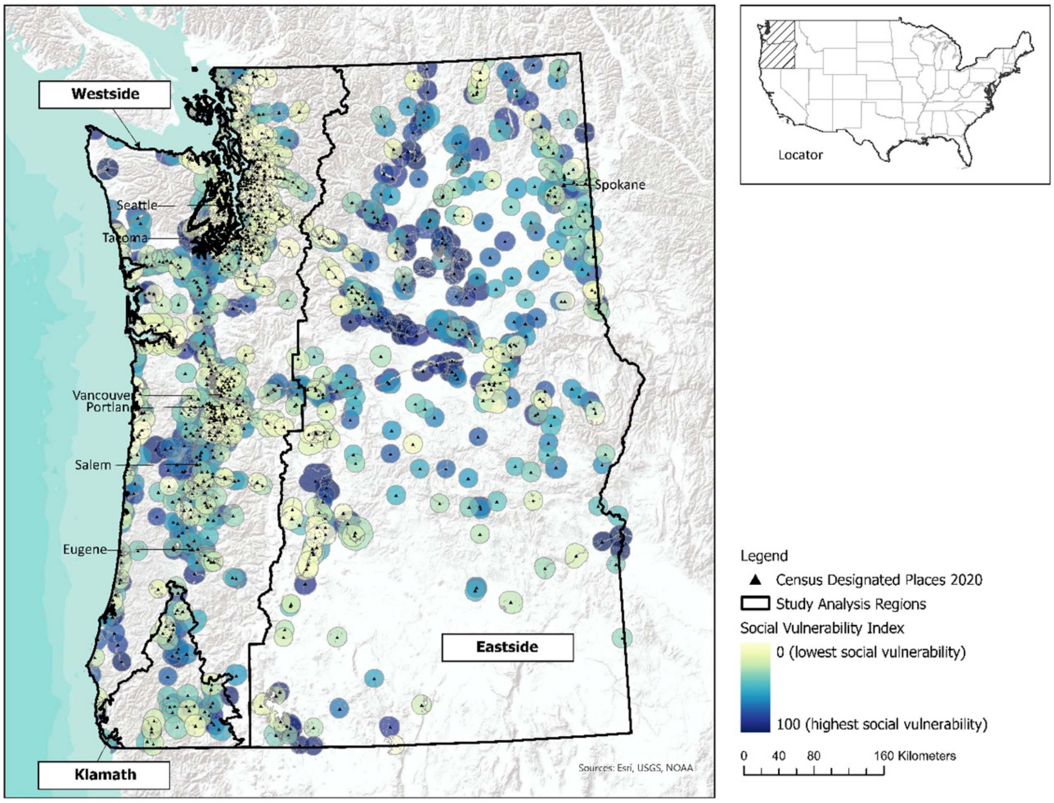

Figure 2. Map of the study area depicting social vulnerability of communities. Each community is a 2020 Census Designated Places (CDPs) with a 10 km buffer drawn from the CDP boundary (area of water removed for analysis). Analysis was separated into westside ($n = 636$ communities), Klamath ($n = 46$ communities), and eastside ($n = 346$ communities) regions. Social vulnerability data was compiled from the US Census Bureau American Community Survey 5-year estimates from 2016 to 2020. 2020 CDP boundaries were retrieved from the US Census Tiger/line shapefiles. The Klamath region boundary was acquired from the US EPA level III ecoregion dataset.

in wildfire management and are further defined in table 1.

Data on ignitions and escaped fires were acquired from the USFS Fire Program Analysis Fire Occurrence Database [49] which spans from 1992 to 2021 and large fire perimeters from 1984–2021 were acquired from the Monitoring Trends in Burn Severity (MTBS) program dataset [50]. We set the threshold for escaped fires at 121 hectares because the USFS defines fires exceeding initial attack capabilities at this size [51]. The cutoff for large fires was determined by the data source (MTBS), which defines large fires in the western US as those greater than 404 hectares [52]. See supplementary materials (figure S4.2) for maps of community wildfire risk and experience variables.

2.2.2. Social vulnerability

Community social vulnerability was estimated following the methodologies of the Centers for Disease Control and Agency for Toxic Substances and Disease Registry social vulnerability index (SVI) [56] which was initially developed by Flanagan *et al* [57] for disaster risk management. This SVI combines 15 socioeconomic variables from the US Census producing a percentile rank ranging from 0 (least vulnerable) to 100 (most vulnerable) for each community. We constructed the index for all communities (2020 CDPs) in Oregon and Washington separately using the American Community Survey 5 year estimates for 2016–2020. For a more detailed discussion on our choice to use CDPs as the unit of analysis see supplementary materials (S1. Community Boundaries). For more details on the methods and indicator variables used to calculate SVI, see the supplementary materials (S.2 Data and Summary Statistics).

2.2.3. Environmental variables

We partially accounted for variation in the fire environment across the study region by analyzing three separate geographic regions based on ecological characteristics and historical fire patterns (eastside, westside, and Klamath—see figure 2). We gathered additional environmental covariates for climate, vegetation, and fire management for consideration in models of community wildfire experience. Climate variables thought to impact fire activity were calculated from the Parameter-elevation Regressions on Independent Slopes Model datasets describing average monthly and annual conditions over the period 1991–2020 [58]. Climate variables calculated for each community included mean annual temperature, annual precipitation, summer (June–August) temperature, summer precipitation, and max vapor pressure deficit (VPD). VPD is the difference between the amount of moisture in the air and how much moisture the air can hold and can be interpreted as the air's 'drying power' [59] which has established links to water stress of vegetation and fuel moisture [60].

Wildfire ignition and spread also has been shown to be sensitive to vegetation type [61–64] and road density [65, 66]. We calculated the proportion of each community classified as forestland, grassland, and developed land from the 2019 National Landcover Database [67]. The density of all roads in each community was calculated using internally acquired data compiled by HERE Technology [68]. We considered two covariates thought to influence success of fire containment efforts: suppression difficulty and fire intensity. Mean suppression difficulty was computed using a suppression difficulty index (SDI) which quantifies the relative difficulty of performing fire control work based on topography, fuels, and expected fire behavior under severe fire weather conditions [69]; mean fire intensity (flame-length probability) was calculated from estimated flame length generated from a custom Pyrologix utility called WildEST [70]. Finally, we assigned each community a designation in one of 12 level III Environmental Protection Agency Ecoregions, which denote areas of general similar geology, physiography, vegetation, climate, soils, land use, wildlife, and hydrology [71], and in one of 75 counties within the study area. These variables were used to account for socioeconomic and ecological similarities across communities located near one another.

More details and tables reporting summary statistics for all variables used in analysis can be found in the supplemental materials (tables S2.1–S2.5).

2.3. Statistical analysis

We evaluated trends in the distribution of simulated wildfire risk related measures compared to observed wildfire experience relative to social vulnerability for all communities across the study area. We then used regression analysis to estimate the likelihood of ignitions, escaped fires, and large fires as a function of social vulnerability for the 1028 communities for which data were available. All wildfire experience measures were estimated using Generalized Linear Mixed Models (GLMMs) using the lme4 package of the R statistical environment [72]. Community-level observations of wildfire experience are not necessarily independent as communities located near one another may be socially or ecologically similar. We included both ecoregion and county as random group effects to account for spatial autocorrelation associated with ecoregion type (e.g. vegetation) and county level administrative policies. All models were estimated using either Poisson or negative binomial probability distributions, depending on whether overdispersion was present, and accounted for the variation in area of land for each community as an 'offset' variable, thus modeling the rate of fire events per area as opposed to true counts. We evaluated full models that included all environmental variables and then created parsimonious models using model selection procedures that minimized Akaike's information criterion (AIC). We assessed the relative importance (RI) of each predictor in final models in two ways. First, we used a common practice of standardizing all predictor variables by their mean and standard deviation, then divided the estimates for each predictor by the standard error of the estimate to get an idea of the RI of each variable that incorporates both the effect size and uncertainty in the estimate. Second, we assessed the partial R-squared to understand the proportion of variance explained for each predictor. Detailed descriptions of our regression and variable importance analysis can be found in the supplementary materials (S3).

3. Results

What is the relationship between community social vulnerability and simulated wildfire risk related measures derived from fire models as compared to actual observed community wildfire experience?

We found that across Oregon and Washington, communities indicated as having greater social vulnerability (those in the top two social vulnerability quartiles) tended to have lower average BP, WHP, and RPSs, as compared to their less socially vulnerable counterparts. This relationship appeared consistent across eastside, westside, and Klamath regions (figure 3, parts (a), (b), and (c)). In contrast, social vulnerability exhibited a more varied relationship with community wildfire experience. Initial visual inspection of fire experience data suggested no clear trends between social vulnerability and exposure to ignitions in any of the three study regions (figure 3, part (d)), nor between social vulnerability and exposure to escaped fires in the Klamath, or large fires across both the westside and Klamath study regions (figure 3, parts (e) and (f)). However, these figures do suggest a positive trend observed between social vulnerability quartiles and escaped and large fires on the eastside (figures 3, parts (e) and (f)), and a slight positive trend between social vulnerability and escaped fires on the westside (figure 3 part (e)). We explore these trends more formally in subsequent regression analyses.

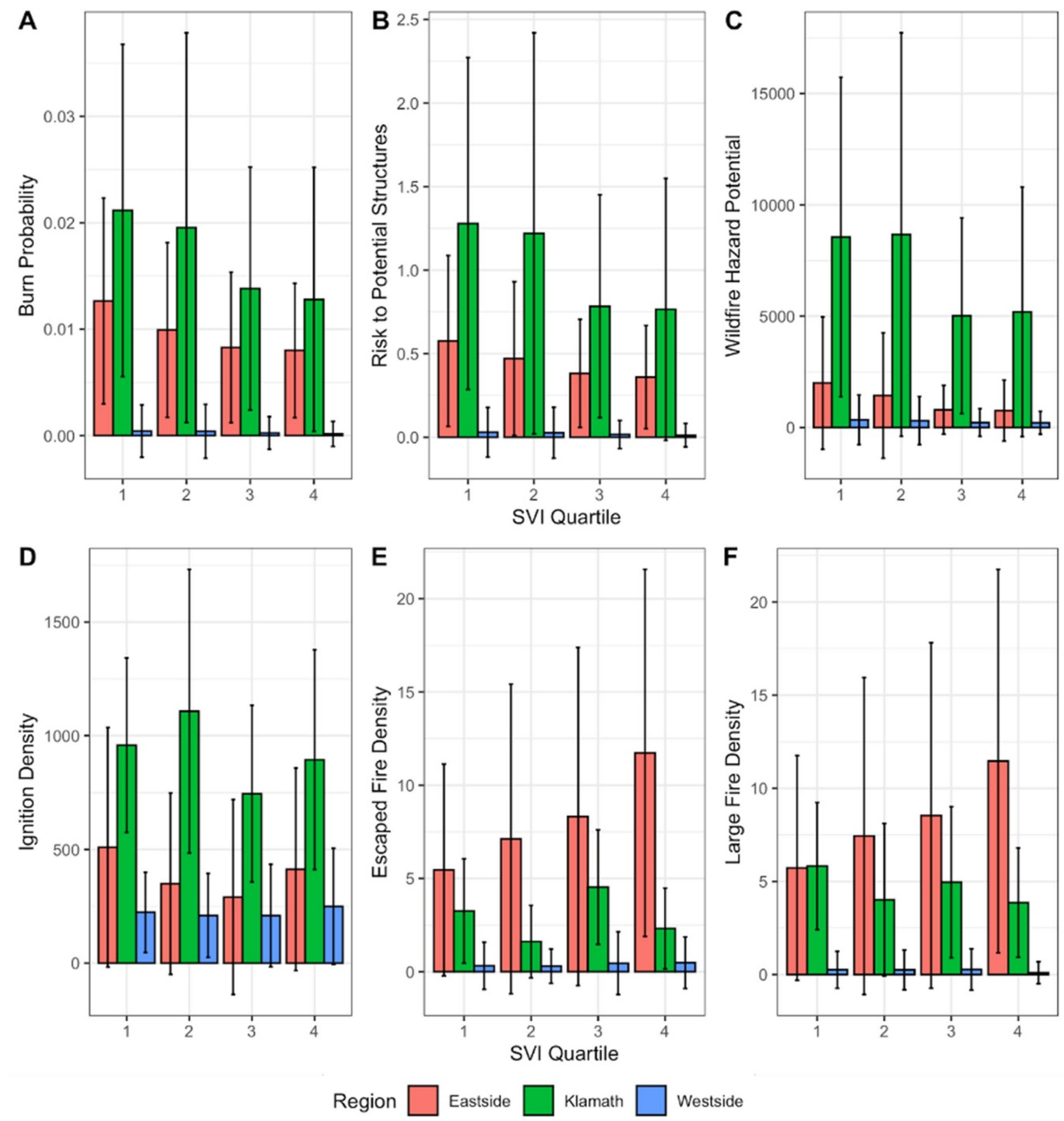

Figure 3. Distribution of simulated wildfire risk related measures and observed wildfire experience relative to community social vulnerability for each analysis region: a) wildfire hazard potential (an index that quantifies the relative potential for wildfire that may be difficult to control), (b) risk to potential structures (integrated measure of hazard with generalized consequences to homes) and c) burn probability (likelihood of fire occurring), (d) mean ignition density (fires km^{-2}), (e) mean escaped fire density (1000 fires km^{-2}) and (f) mean large fire density (1000 fires km^{-2}). Zero observations were removed to make trends easier to see (trends were the same when zeros were included). Data from Dillon & Gilbertson-Day [48]; Nelson [50]; Scott *et al* [51]; Short [70].

What is the relationship between community social vulnerability and community exposure to ignitions, escaped fires, and large fires?

Our regression models allowed us to assess the statistical significance of correlations between social vulnerability and community exposure to ignitions, escaped fires, and large fires, while also accounting for regional variations in climate, vegetation, and fire management (i.e., environmental variables presented in section 2.2.3). We note that observational studies cannot establish causal relationships, but rather can identify correlations between a dependent variable and independent variables. We focus on interpreting the observed correlations between social vulnerability, our variable of interest, and various types of community wildfire experience. Instead of reporting regression coefficients representing the difference between the log of expected counts, which can be difficult to interpret, we report the incidence rate ratio (IRR), or the effect of independent variables on the dependent variable expressed in terms of a percentage increase or decrease, with the precise percentage determined by the amount the IRR is either above or below one [73].

Our eastside regression model results indicate that, after controlling for variation in the fire environment, community social vulnerability was significantly associated with a higher likelihood of experiencing ignitions, escaped fires, and large fires ($p < 0.05$). A 10-point increase in a community's SVI score resulted in a four percent increase in the likelihood of ignitions, six percent increase in the likelihood of escaped fires, and three percent increase in the likelihood of large fires (IRR = 1.04, 1.06, 1.03, respectively) (table 2). Across the westside, we observed positive estimated coefficients for the social vulnerability variable in the models for ignitions and escaped fires and a negative coefficient for large fires. Neither of these were statistically significant ($p < 0.10$) (table 2). Across the Klamath, the estimated coefficients for social vulnerability also tended to be positive but were not statistically significant ($P > 0.10$) (table 2).

Comparing the importance of independent variables on community wildfire experience is difficult based on the estimated coefficients alone as variables were measured on vastly different scales. We assessed RI and partial R^2 to understand the relative effect size and proportion of variance explained by our environmental covariates as compared to social vulnerability (table 3). On the eastside, social vulnerability (SVI) was not as important in explaining community experience with ignitions (RI = 2.00) as road density (RI = 4.29) and the proportion of forested landcover were (RI = 6.00) (table 2). Social vulnerability status was almost as important as VPD and suppression difficulty (SDI) (SVI RI = 5.33, VPD RI = 6.27, SDI RI = 6.75) in explaining escaped fires, but SVI explained a relatively small proportion of the variance (3% as opposed to 9% and 11%, respectively) (table 3). VPD and suppression difficulty were more important relative to social vulnerability status in predicting exposure to large fires on the eastside (VPD RI = 6.45, SDI RI = 5.75, and SVI RI = 2.67 respectively). On the westside, road density was especially important in predicting ignitions, while suppression difficulty was the most important predictor of escaped fires, and VPD was the most important in predicting large fires. Across the Klamath, summer temperature was the most important predictor of ignitions, followed by the proportion of forestland, while suppression difficulty was the most important predictor in escaped and large fire models (table 3).

4. Discussion

Our results suggest that the biophysical and management environment (e.g. road density, proportion of forestland, and suppression difficulty) has a significant influence on the likelihood of ignitions, escaped fire, and large fires, consistent with previous research. However, we also found that social vulnerability plays a critical role in shaping a community's wildfire experience. In the Pacific Northwest, we observed that eastside communities with *higher* social vulnerability tended to have a *higher* likelihood of experiencing ignitions, escaped fires, and large fires. This contrasts with measures of *simulated* wildfire hazard and risk, where communities with *lower* social vulnerability tended to have *higher* measures of hazard and risk, aligning with prior studies conducted nationally and across the western US [24, 37, 39]. We suspect this is because amenities that increase property values (e.g. recreation access, forested viewsheds, desirable climate) tend to be correlated with the biophysical characteristics that also increase wildfire hazard (e.g. forests and open space, complex topography, sunny and drier weather). Our findings, consistent with previous research [40, 46, 74, 75], suggest that pre-existing social inequities can exacerbate wildfire risk, leading to disproportionate exposure for communities with limited resources.

While our westside and Klamath regions did not demonstrate the same statistically significant correlations with fire experience, we observed consistent positive associations between social vulnerability and community fire experience in both regions, except for large fires occurring on the westside of the Cascades (table 2). This suggests that the main disparity lies in the variability and statistical significance associated with datasets with fewer communities (as observed in the Klamath region) and fewer escaped and large fires (as observed on the westside), as sample size influences statistical power.

The lack of statistical significance may also be attributed to the unique social and environmental characteristics of each region. For instance, the Klamath region features highly fire-prone and productive forests, with population centers concentrated in valleys along major transportation routes resulting in communities with varying levels of social vulnerability being simultaneously exposed to wildfires. This makes it challenging to isolate relationships between community level social vulnerability and wildfire experience, as more socially vulnerable communities likely benefit from nearby, better-resourced communities. On the westside, historical fire patterns show longer intervals between events compared to other regions, particularly under contemporary fire management practices. Large fires in this area are often driven by extreme weather events, such as the dry, high-wind conditions seen during the Labor Day fires of 2020 [76]. These weather phenomena, combined with the substantial fuel loadings in these highly productive ecosystems, likely overshadow any discernible differences in fire response capacity, prevention, and mitigation efforts, even if such differences exist.

Table 2. Incident rate ratio[a] (IRR) and heteroskedasticity robust standard error in parenthesis for final models of ignitions, escaped fires, and large fires.

	Eastside ($n = 346$)			Westside ($n = 636$)			Klamath ($n = 46$)		
	Ignitions[c]	Escaped fires[d]	Large fires[d]	Ignitions[c]	Escaped fires[d]	Large fires[d]	Ignitions[d]	Escaped fires[d]	Large fires[d]
(Intercept)	0.01 (0.85)***	0.00 (0.59)***	0.00 (−0.59)***	0.38 (0.29)***	0.00 (0.75)***	0.00 (−2.30)***	0.00 (0.37)***	0.00 (1.01)***	0.00 (−2.33)***
Social vulnerability (index 0–10)	1.04 (0.02)**	1.06 (0.01)***	1.03 (−0.01)**	1.02 (0.01)	1.08 (0.04)*	0.89 (−0.06)*	1.00 (0.00)	1.03 (0.05)	1.03 (−0.04)
Road density (km^2)	1.41 (0.08)***			0.74 (0.02)***			1.15 (0.01)***		
Max vapor pressure deficit	1.06 (0.05)	1.24 (0.03)***	1.24 (−0.04)***			1.80 (−0.20)**			1.37 (−0.09)***
Proportion forestland (%)	1.02 (0.00)***			1.01 (0.00)***			1.01 (0.00)***		
Suppression difficulty		1.03 (0.00)***	1.02 (0.00)***		1.02 (0.01)**	1.03 (−0.01)**		1.02 (0.01)**	1.02 (−0.01)***
Summer precipitation (mm)				0.99 (0.00)**	0.98 (0.02)			1.05 (0.03)	
Summer temperature (C)							1.57 (0.02)***		
Annual temperature (C)									0.72 (−0.19)
Pseudo R^d	0.38	0.17	0.11	0.71	0.03	0.14	0.47	0.16	0.61
AIC	3957.16	1652.26	1491.59	6323.98	503.67	289.89	966.01	124.56	146.78
Log Likelihood	−1970.58	−820.13	−739.79	−3153.99	−245.84	−138.95	−477.00	−57.28	−67.39
Var: County[a]	0.66	0.42	0.63	0.39	1.79	3.12	0.09	0.46	0.00
Var: Ecoregion	0.00	0.08	0.08	0.07	0.22	0.90			

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Note. 8 ecoregions and 37 counties in the eastside, 6 ecoregions and 36 counties in the westside, 3 counties and 1 ecoregion in the Klamath. SVI was rescaled to 0–10 aid with interpretation and IRRs represent a 10-unit change in SVI. All models use area of land in km^2 as an offset, thus modeling rates (fires/area of land) as opposed to counts.

[a] The IRR, or the effect of independent variables on the dependent variable expressed in terms of a percentage increase or decrease, with the precise percentage determined by the amount the IRR is either above or below one 1.

[b] The variance across groups for the random intercept variables is reported in the table.

[c] model with negative binomial distribution and log link function.

[d] model with Poisson distribution and log link function.

Table 3. Variable importance.

	Eastside ($n = 346$)						Westside ($n = 636$)						Klamath ($n = 46$)					
	Ignitions		Escaped fires		Large fires		Ignitions		Escaped fires		Large fires		Ignitions		Escaped fires		Large fires	
Fixed effects	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$	RI	${R_\beta}^2$
Social vulnerability (0–10)	2.00	0.01^{**}	5.33	0.03^{***}	2.67	0.01^{**}	1.33	0.00	1.92	0.00^{*}	1.83	0.00^{*}	1.00	0.00	0.71	0.01	0.73	0.00
Road density (km^2)	4.29	0.06^{***}					15.80	0.39^{***}					9.25	0.06^{***}				
Max vapor pressure deficit	1.18	0.01	6.27	0.09^{***}	6.45	0.09^{***}					2.92	0.01^{**}					3.43	0.67^{***}
Proportion forestland (%)	6.00	0.16^{***}					5.14	0.07^{***}					13.50	0.19^{***}				
Suppression difficulty			6.75	0.11^{***}	5.75	0.08^{***}			2.50	0.00^{**}	2.08	0.00^{**}			3.07	0.18^{**}	4.27	0.22^{***}
Summer precipitation (mm)							3.00	0.03^{**}	1.52	0.01					1.42	0.03		
Summer temperature (C)													26.67	0.51^{***}				
Annual temperature (C)																	1.74	0.31

Note. Relative importance (RI) is calculated as the standardized predictors divided by the standard error of the estimate (RI = scaled estimate/SE). This approach incorporates uncertainty in the estimate along with the effect size.
${R_\beta}^2$ = a standardized measure of multivariate association between the fixed predictors and the observed outcome. This method was introduced by Edwards *et al* (2008) and calculated using the r2glmm package in R.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

Based on our results, we reason that social status and access to resources may moderate risk and influence wildfire experience. Prior research investigating causes of ignition in the Pacific Northwest indicated that nearly half of all ignitions on the eastside are human-caused, and the vast majority are accidental, often originating from individuals recreating or burning debris, or by vehicle and equipment use [77]. Wildfire prevention focuses on reducing ignitions through community education programs that aim to alter human behaviors that drive ignitions (e.g. operating heavy machinery in high fire risk conditions) [78]. Targeted prevention initiatives may indeed reduce community exposure to ignitions, and subsequently larger wildfires across the region. Our finding that social vulnerability is associated with a higher likelihood of experiencing ignitions east of the Cascade Range, and potentially west of the Cascades as well, suggests that current prevention measures are either insufficient or ineffective for some reason—possibly because prevention and education measures are focused on high-risk communities in the Wildland Urban Interface with lower social vulnerability [79, 80].

Furthermore, wildfire mitigation aims to reduce fire impacts by reducing hazardous fuels through mechanical treatments, cultural burning, prescribed burning or management of the home ignition zone. Wealthier communities are more likely to be able to mobilize and secure grants for fuel reduction projects and may have more social and political capital to influence decisions related to strategic pre-fire planning, both of which can influence success of fire operations when fires do occur. In the US, individuals are largely responsible for conducting risk mitigation activities on their own property, and standard approaches to reducing risk to homes, such as retrofitting with fire resistant materials or trimming trees in the home ignition zone, can be costly [81]. Thus, communities of higher socio-economic status are likely better able to overcome risks associated with living in wildfire prone areas, because they are better able to undertake wildfire prevention and risk mitigation measures.

Additionally, prior research has demonstrated that escaped fires and their growth are driven by fire weather and other biophysical factors [82, 83], and that strategic suppression efforts can substantially affect outcomes [84]. The increased likelihood of experiencing escaped and large fires across more socially vulnerable communities in highly fire prone landscapes suggests those communities may have under-resourced fire response units, often relying on volunteer rural fire departments or Rangeland Fire Protection Associations [85, 86]. While there is limited research investigating the distribution of wildfire response resources relative to community socioeconomic status, both Oregon and Washington have fire protection districts funded in part through income and property taxes which would lead to differences in response capacity [87, 88]. This is particularly evident in our study region given the loss of timber tax revenue, leaving many counties more reliant on property taxes to fund emergency response services [89, 90].

We also suspect that the likelihood of neighborhood sorting, wherein individuals gravitate or are steered by socioeconomic forces (housing affordability, social networks, access to opportunities) into more economically segregated communities [91], results in areas with lower incomes and home values generating reduced capital through local taxes, and thus leading to limited resources for essential services that can influence wildfire outcomes. Adequate funding for firefighting resources is vital for protecting communities and underfunded programs appear to translate to greater exposure to larger fires. We reason that tying these services to the local tax base may result in communities with lower incomes and property values generating less revenue to invest in fire response and management.

We recognize that quantifying complex social phenomena such as social vulnerability poses several challenges [44, 92, 93]. In our study in particular, these difficulties stem from limitations in data availability and the complexity of compiling a comprehensive time series dataset covering all communities given the changes in CDP boundaries over the decades analyzed. In addition to examining social vulnerability trends, we also explored connections between home value and community wildfire experience. Higher home values were associated with increased numbers of wildfire ignitions across communities in the Klamath and eastside regions, but were associated with fewer escaped and large fires, suggesting that while wealthier communities are more prone to accidental ignitions, presumably due to their location in higher hazard areas, they also have more resources to prevent those ignitions from escaping and becoming larger, more destructive fires (see supplementary material, figure S4.1). It would be useful to further explore the components of social vulnerability (e.g. poverty status, minority status, housing type, etc) relative to wildfire risk and experience. Such research could provide additional insight into the way individual socioeconomic factors influence vulnerability and risk, information that may be lost when using a composite index that combines many individual indicators into a single score.

While factors accounting for the physical fire environment (i.e. VPD, suppression difficulty, road density, landcover, temperature, and precipitation variables) were relatively more important than social vulnerability in predicting variation in community level wildfire exposure, our findings underscore the importance of incorporating human factors into comprehensive risk metrics, particularly when evaluating community-level investments aimed at improving wildfire response capabilities. We argue that the risk and hazard metrics commonly used to prioritize wildfire resources fail to consider crucial human factors related to wildfire prevention and response. For example, the models utilized to estimate fire hazard employ simplified fire suppression rules that assume equal and adequate fire response, which our analyses suggest is not appropriate. Additionally, WHP [36] assumes extreme fire behavior is the only factor that challenges suppression success, ignoring the influence of social factors that impact response capacity. Our analyses suggest that the overreliance on these metrics for the distribution of finite resources could leave more socially vulnerable communities exposed to wildfire than desired by policy makers.

Although delving into disparities in community resource allocation is beyond the scope of this paper, we believe that it represents a crucial avenue for future research into the determinants of community fire experience. Furthermore, as we contend that the connection between social vulnerability and exposure to escaped and large fires in particular is influenced by disparities in fire response capacity, analyses on land ownership and agencies responsible for wildfire response can aid in identifying areas with inadequate resources for community protection. Collectively, this information can improve and guide targeted investments at the appropriate level of governance.

5. Conclusion

Our analysis of social vulnerability, wildfire risk, and wildfire experience allowed us to examine differences between predictions of risk to communities and actual community fire experience, and to determine possible correlations between social vulnerability and various dimensions of community-level wildfire experience in the Pacific Northwest. While biophysical factors had greater influence on wildfire experience, we found that communities located in areas where simulated measures of wildfire risk and hazard are highest were on average less socially vulnerable, but that when controlling for differences in the fire environment, more socially vulnerable communities across eastside landscapes had a higher likelihood of experiencing ignitions, escaped fires, and large fires than their less vulnerable counterparts. These trends appear to be emerging among westside communities as well in terms of escaped fires.

Given that policy goals often focus on ensuring vulnerable populations are not disproportionately affected by adverse environmental hazards (e.g. Executive Order 12 898 [89] and Executive Order 13 985 [90]), our findings have implications for policy and decision makers. First, our finding that communities subject to higher measures of hazard and risk generally are wealthier and better resourced raises the question of whether current risk assessment measures might perpetuate social inequities by encouraging more resources to be devoted to high-risk areas even as more socially vulnerable communities might face disproportionately greater exposure. Second, our finding that, on the eastside, communities with higher social vulnerability and fewer resources tended to have a higher likelihood of exposure to ignitions, escaped fires, and large fires raises further concerns about distribution of mitigation or suppression resources across communities. Absent policy and management changes that address such inequities, such as greater consideration of community socioeconomic factors in wildfire quantitative risk assessment, wildfires may continue to disproportionately burden more vulnerable communities. Given the influx in state and federal funding for community wildfire risk reduction projects [87, 88] and the role of quantitative risk assessment data and maps in allocating those resources, risk scientists, policymakers, and agency decision-makers with authority to allocate scarce wildfire resources may need to consider how best to integrate measures of social vulnerability into risk assessments and management decisions.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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