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Geographic multi-criteria evaluation and validation: A case study of wildfire vulnerability in Western North Carolina, USA following the 2016 wildfires

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ABSTRACT

In 2016, an intense drought occurred in the southeastern U.S. Dry conditions resulted in unprecedented wildfires throughout the southern Appalachian Mountains, especially in western North Carolina (WNC). Future climate change is expected to increase temperatures, alter precipitation, and stress water resources in the region, which could lead to more frequent drought and wildfire. The increasing threat of destructive wildfires combined with a growing wildland-urban interface indicate a need for a comprehensive assessment of wildfire vulnerability in WNC, while recent wildfires offer an opportunity to evaluate assessment accuracy. The study identifies locations vulnerable to wildfire in WNC based on wildfires from 1985 through 2016. By combining tract-level socio-economic and physical data in a geographic information system, specific locations of vulnerability were identified and validated using wildfire perimeters from 2016. Unlike previous vulnerability research, this study integrates novel methods in GIS, including analytical hierarchical processing, validation, and GIS multi-decision criteria decision making to ensure vulnerability is accurately calculated. The vulnerability index indicates that social vulnerability varies greatly throughout the region, while physical and overall wildfire vulnerability is greatest in rural, mountainous portions of the region, which are less equipped for mitigation. Based on the results, the impacts of future wildfires on quality of life will vary across the region, so targeted responses are needed. The vulnerability index provides transparency to vulnerable communities, enabling policymakers to identify opportunities to prepare for resilience by targeting vulnerability hotspots.

1. Introduction

1.1. Wildfire in Appalachia

According to the Food and Agriculture Organization of the United Nations [55], a wildfire is "any unplanned and/or uncontrolled vegetation fire." While fire-dependent ecosystems rely on fire, fire-sensitive ecosystems rely on fire suppression [1]. Throughout Appalachia, wildfire and wildfire management practices have played an integral role in forest development. Prior to suppression in the twentieth century, fire intervals averaged between 6 and 8 years, influencing vegetation development. As a result of reduced fire, oak and pine species are being replaced by more fire-sensitive species, changing the characteristics of forests and making wildfires more intense [2]. Throughout the past few decades, wildfire management has changed due to increases in season length, fire size, acreage burned, and extreme behavior [61].

Though wildfires are beneficial to forest ecosystems, it threatens communities in the wildland-urban interface (WUI), the area where houses meet or intermingle with undeveloped wildland vegetation [3]. WUI development contributes to wildfire vulnerability, as well as emergency management challenges. Previous studies have demonstrated a relationship between human activities and wildfire presence. Specifically, populations and roads affect the likelihood of wildfire occurrence internationally and in Appalachia [4–8]. Additionally, wildfires resulting from human activities burn more area and occur more often compared to naturally-caused wildfires [9].

The complex climate and topography of mountainous regions influences wildfire. Dry conditions and locations elevate wildfire frequency and intensity (e.g., Refs. [2,9,10]). Lafon et al. [9] identified four characteristics of fire in Appalachia: humid temperature conditions supporting fuels; seasonal variations in weather causing pronounced seasonality; periodic dry years with favorable burning conditions and wet years with less favorable conditions; and frequent coincidences of lightning and dry conditions to ignite fires during the growing season. Lafon and Grissino-Mayer [11] determined the Blue Ridge was particularly fire prone compared to other physiographic provinces of Appalachia based on ignition density, maximum fire size, and fire cycle. Wildfire predictors also vary locally, requiring place-based analyses of

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wildfire vulnerability [4]. Because fire is sensitive to climate, future variability will likely influence wildfire patterns.

There is less consensus on how topographic variables influence wildfire and the strength of topographic trends vary according to the climate. Flatley et al. [10] determined that fire occurrence was highest at dry, south-facing slopes, ridges, and low elevations at the Great Smoky Mountains and Shenandoah National Parks in the Southern and Central Appalachians with elevation having the greatest influence and aspect having the least. Maingi and Henry [7] determined that fire occurrence was highest at higher elevations and on steeper slopes in eastern Kentucky. Lein and Stump [6] determined that fire occurrence was highest at sites with high deciduous fuels, high solar radiation, low topographic wetness, flatter slopes, and low population density in the Appalachian Mountains of southeastern Ohio. The range of findings demonstrates the complexity of pinpointing wildfire vulnerability in mountainous locations, as well as the need for studies comparing drivers of wildfire in all regions of Appalachia.

1.2. Social vulnerability and wildfire

The concepts of vulnerability, adaptation, and resilience are used throughout scientific literature to describe biotic systems. A variety of definitions exist for the three terms, but all three describe the response to changes in the relationship between open, dynamic systems and their external environments [12]. Vulnerability varies spatiotemporally, making it geographical in nature [13]. Vulnerability can be a result of biophysical risks, social responses, or hazards of place [14]. Cutter [14]'s hazards of place model of vulnerability conceives vulnerability as both a biophysical risk and social response framed by geographical location. The hazards of place model suggests that vulnerability is closely related to the socioeconomic and physical characteristics of a location and changes over time.

The influence of social vulnerability on a system's ability to respond to natural hazards is well-established. However, methods for evaluating social vulnerability to natural hazards vary. The foundational vulnerability index is Cutter et al. [15]'s Social Vulnerability Index (SoVI), an index of social vulnerability to natural hazards. The SoVI is valuable because it produces illustrations of the uneven capacity for preparedness and response, which can be used to inform programs and policies [16]. The SoVI has been widely used to study exposure to hazards, including drought, flooding, and sea level rise, both nationally and internationally (e.g., Refs. [17–19]). Some studies have constructed social indices similar to the SoVI to specifically evaluate wildfire vulnerability by taking variables relating to poverty, race, gender, and education into account. Davies et al. [20] determined that census tracts with majority Black, Hispanic, and Native American populations experience 50% or greater wildfire vulnerability compared to other tracts across the U.S. Additionally, these results indicated moderate wildfire hazard and high social vulnerability scores throughout the southeast compared to other regions in the U.S. Similarly, Wigtil et al. [21] created a wildfire vulnerability index for the coterminous U.S. based on the SoVI and determined that the highest percentage of intersections between social vulnerability and wildfire potential occurred in the southeastern U.S.

Specific socioeconomic variables have been associated with wildfire vulnerability. Feltman et al. [5] determined that wildfire occurrence was positively correlated with low road densities, low population densities, low population changes, high poverty rates, and low educational attainment in South Carolina. Of these variables, poverty and education had the largest influence on wildfire occurrence, indicating the importance of socioeconomic variables to wildfire vulnerability studies. Similarly, Gaither et al. [22] examined the influence of fire mitigation programs in the southeastern U.S. and determined that poorer communities with high fire risk are at a greater disadvantage than more affluent communities with comparative fire risk in their states, highlighting an important environmental justice issue.

A shortcoming of many existing vulnerability studies is their lack of validation [23]. Cutter et al. [15] suggested refinements to the SoVI, including the integration of hazard event frequency data. Additionally, many vulnerability studies are conducted at the regional, state, or county level (e.g. Refs. [13,15,17]), and emphasize the importance of examining vulnerability at a local scale (e.g., Ref. [14]). The SoVI is a comparative metric, so results vary based on the size and characteristics of the study area [16]. Sub-county level evaluation of vulnerability facilitates more effective policymaking by pinpointing local vulnerabilities, which is particularly valuable in complex regions like Appalachia.

1.3. The 2016 wildfires

In November of 2016, dozens of intense wildfires burned throughout Southern Appalachia in the southeastern U.S. The wildfire outbreak was supported by a combination of extremely dry conditions, ideal topographic characteristics, high fuel loads, and arson [24]. The large-scale wildfires, resembling those occurring in the western portion of the country, were unprecedented for Appalachia. The fires burned into the dry canopies, roots, and even riparian banks and spread quickly as winds and temperatures increased [25]. The worst case scenario occurred when the wildfires spread into the popular tourist destination, Gatlinburg, Tennessee, destroying much of the town. Residents rapidly evacuated and air quality alerts were issued for much of the East Coast. In 2016, forestry professionals, emergency responders, government officials, and local residents were ill-prepared to respond to the wildfire outbreak. Past wildfire outbreaks offer an opportunity to understand, predict, and prepare for wildfire in Appalachia.

Western North Carolina was particularly impacted by the wildfires in 2016. The region's aesthetic beauty and rich biodiversity have made the region a destination for tourists, as well as new residents. Increasingly, the growing population has settled into the WUI, and dramatic modification of the natural environment has contributed to enhanced drought and wildfire risk. In 2016, the active wildfire season resulted in significant economic losses for local business owners in the agricultural and tourism sectors of western North Carolina [26]. The large rural population was particularly impacted by the dry, smoky conditions throughout the region. Projected temperature increases and precipitation variability could further stress water resources in the region, causing more frequent and intense drought and wildfire events [1,27]. The combination of environmental conditions increasingly favorable for wildfire with a large rural population dependent on the mountain landscape suggest elevated wildfire vulnerability in western North Carolina.

Currently, the success of wildfire mitigation planning is limited by inadequate characterization of physical risk, lack of emphasis on socioeconomic drivers, and incomplete integration of the two [28]. The increasing threat of destructive wildfires combined with the growing WUI indicate a need for a comprehensive assessment of wildfire vulnerability in western North Carolina, while recent wildfires offer an opportunity to evaluate the accuracy of the assessment. Due to uncertainty about future climate changes, implementing proactive policies is crucial [1]. Since fire risk is a combination of likelihood, intensity, and effects, models evaluating vulnerability to wildfire serve research and management needs [4].

The objective of the present study is to identify locations vulnerable to wildfire in western North Carolina. By combining socioeconomic and physical data in geographic information systems (GIS), specific locations of vulnerability can be identified and evaluated using information about the wildfire outbreak in 2016. Using statistical analyses, the regional drivers of wildfire can be determined. Unlike previous vulnerability research, this study will integrate novel methods in GIS, including analytical hierarchical processing, validation, and GIS multi-criteria decision-making (MCDM) to ensure vulnerability is accurately calculated. The results of the proposed study will provide transparency

to vulnerable communities, as well as enable policymakers to prepare for resilience to wildfire in western North Carolina.

2. Study area

The study focuses on census tracts in the 27 westernmost counties of the state of North Carolina, USA. Tracts are small, relatively permanent statistical subdivisions of counties delineated by the U.S. Census Bureau [59]. Tracts are ideal administrative boundaries for vulnerability studies because they are the smallest geographies with detailed socioeconomic data available, as demonstrated by Davies et al. [20].

Based on shapefiles of wildfire boundaries obtained from the Geospatial Multi-Agency Coordination (GeoMAC) [29], approximately 75,000 acres of these counties burned from late October through early December 2016. Western North Carolina is not typically the focus of wildfire studies, despite being particularly impacted by the events in 2016. This is highlighted in comparison to regions with frequent wildfire outbreaks, such as Southern California. Additionally, Western North Carolina is experiencing increasing hydroclimate variability, which could exacerbate wildfires in the future [30].

Western North Carolina is often characterized by its complex physical characteristics, and is an important source of water for the surrounding region, including large metropolitan cities like Charlotte, North Carolina and Atlanta, Georgia. The region is divided into two physiographic provinces: the Blue Ridge and the Piedmont, which are separated by the Blue Ridge Escarpment. The Blue Ridge province is characterized by a rugged landscape. The escarpment and associated elevation gradient result in climatic variability throughout western North Carolina [31]. For example, precipitation ranges from less than 40 inches annually in Buncombe County to more than 100 inches in the neighboring Transylvania County [57].

Western North Carolina's overall median household income is below the state and national averages. Within the region, inequality is particularly prevalent with a nearly $15,000 difference between the highest median household income ($48,138 in Henderson County) and lowest ($33,598 in Swain County) [32]. Additionally, 23 of the 27 counties have a rural population greater than 50% [33]. As a result of these economic differences, development varies greatly across the region. Metropolitan locations, such as Asheville, have elevated economic status and therefore greater capacity for resilience. In contrast, the large rural population throughout the region suggests communication and mobility challenges that elevate vulnerability. Western North Carolina's economic disparity complicates policymaking and highlights a need for local-scale assessments. The region's variability in regards to climate, topography, and economic development drive regional patterns of wildfire (Fig. 1).

3. Methods

In the present study, GIS is employed for MCDM, which is the process of combining information from several criteria to form a single index of evaluation [34]. MCDM requires the creator to make decisions about a variety of factors, including variables, scales, and weights, and these decisions introduce subjectivity to indices [35]. GIS-based methods are increasingly used to inform and validate these decisions [23].

3.1. Social vulnerability

Socioeconomic data was selected based on [16]; who identified the 27 variables as proxies for characteristics known to influence vulnerability to hazards (Table 1). Variables were downloaded from the 2010 Census and 2012-6 American Community Survey (ACS) for 317 census tracts in western North Carolina. ACS data was selected because it was the most current source of socioeconomic data when the analysis was conducted. Only one variable, percentage of population living in nursing homes, was unavailable from the ACS. It was downloaded from the 2010 Census. Three tracts were excluded from the analysis due to lack of population and thus data availability.

In IBM SPSS Statistics 24, the variables were normalized using z-score standardization. To reduce multicollinearity between variables, the standardized scores underwent principal components analysis (PCA). The first 7 components met Kaiser's criterion and were retained and categorized for analysis [36] (Table 2). The directionality of the wealth component was reversed because a higher amount of wealth indicates lower vulnerability. In ArcMap 10.4.1 [54], the components were joined to the tracts and summed to produce the social vulnerability index.

3.2. Physical vulnerability

To assess physical vulnerability, ten variables representing fuels, topography, climate, and development were selected based on previous wildfire studies. Wildfires are highly influenced by the availability of fuels. To represent fuels, land cover data was downloaded from the 2011 National Land Cover Database [37]. Percentage forest cover was derived by combining cells classified as deciduous, evergreen, and mixed forest and dividing them by the total number of cells per tract. Forest biomass data was acquired from the USDA Forest Service's Forest Inventory and Analysis (FIA) Program. FIA biomass data is derived from field data and Landsat satellite imagery and is valuable for measuring forest disturbance and regrowth [38]. In addition to fuels, climate and topography influence patterns of wildfire. The National Elevation Dataset served as the source for one arcsecond elevation data used to produce slope, aspect, and illumination (hillshade) layers [39]. Linear aspect values were computed using the Geomorphometry and Gradient Metrics Toolbox 2.0 [40]. From the PRISM Climate Group, 30-year normals for precipitation and temperature were downloaded [57]. Finally, humans influence wildfire by developing in the WUI. Population density was calculated based on population data from the U.S. Census Bureau [41]. Road density was calculated using a shapefile of statewide system and non-system road routes acquired from the North Carolina Department of Transportation [56] (Table 3).

The subjectivity of weighting decisions can be reduced using methods in GIS, such as the analytical hierarchy process (AHP) [23]. AHP is a theory of measurement through pairwise comparisons that relies on the judgements of experts to derive priority scales [42]. AHP is one of the most popular weighting methods for GIS-based MCDM because it is ideal for decision-making problems involving large amounts of heterogeneous data [23,34]. Previous studies have demonstrated the value of AHP for strengthening natural hazards MCDM, including wildfire risk (e.g., Refs. [43,44]).

To determine weighting and enable validation of vulnerable locations, 2016 wildfires perimeters were obtained from GeoMAC [29] and 1985–2015 (historical) wildfire perimeters were obtained from the USDA Forest Service [60]. The historical wildfires were used to inform the physical index due to the larger sample size compared to 2016. Using the historical wildfire perimeters, presence (1) or absence (0) values were calculated for each census tract in the study area. The mean of each physical variable was calculated for each tract. In RStudio 1.0.143 [58], a Kendall rank correlation and binomial regression were run to evaluate the relationship between the physical variables and the historical wildfires due to the non-linear and non-normal distribution of the data ($\alpha = 0.10$). The results of the binomial regression revealed that road density was the highest predictor of historical wildfire presence and absence. Hillshade, the hypothetical amount of illumination from the sun, was the second highest predictor (Table 4).

Similar to Yalcin et al. [45], the results of the correlation and regression were used to inform the AHP. Based on the direction of the correlation between the physical variables and the historical wildfires, each of the physical variables was reclassified (Table 5). All variables were reclassified into five classes using an equal interval classification

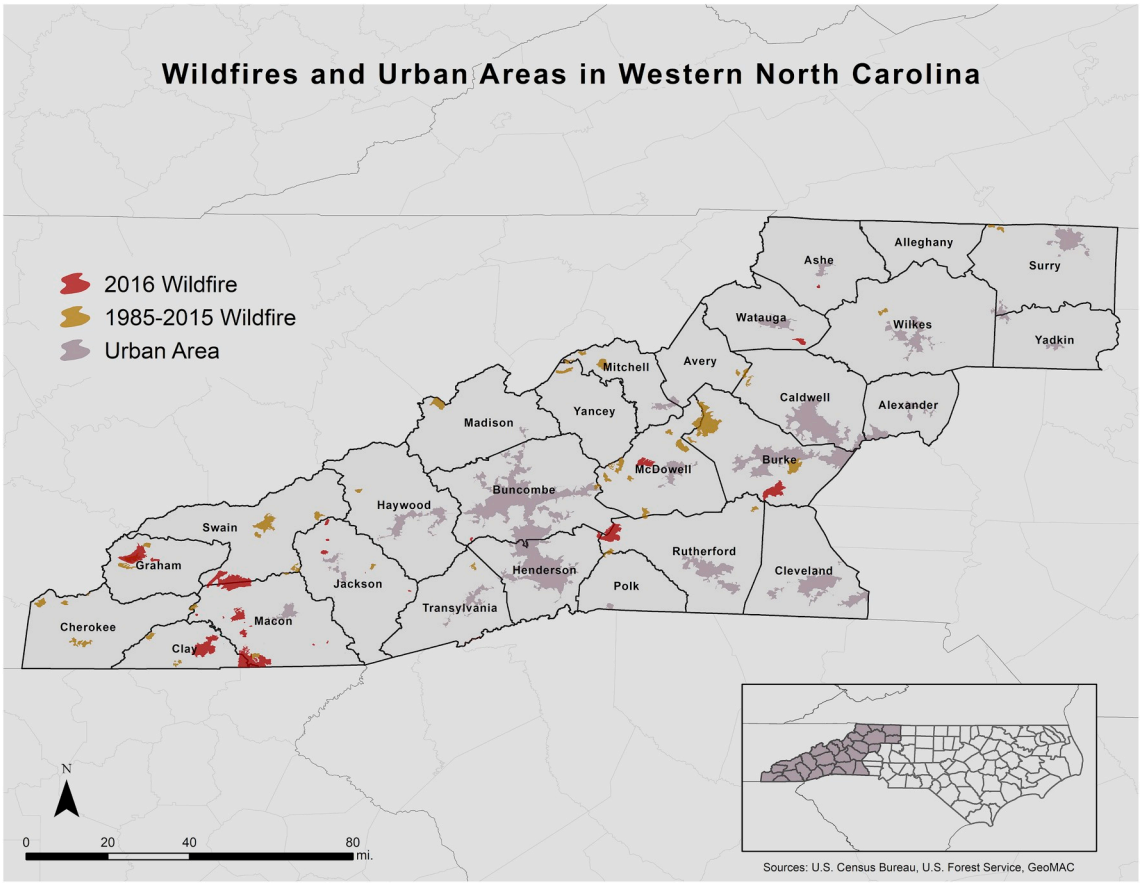

Fig. 1. Wildfire perimeters and census-defined urban areas (50,000 or more people) in western North Carolina, USA (Sources: U.S. Census Bureau, U.S. Forest Service, GeoMAC).

Table 1
The social vulnerability index variables and sources based on the SoVI.

Name	Description	Source
MDGRENT	Median gross rent for renter-occupied housing units	2012-6 American Community Survey
MEDAGE	Median age	
MHSEVAL	Median dollar value of owner-occupied housing units	
PERCAP	Per capita income	
PPUNIT	Average number of people per household	
QAGEDEP	% Population under 5 years or age 65 and over	
QASIAN	% Asian population	
QBLACK	% African American (Black) population	
QCVLUN	% Civilian labor force unemployed	
QED12LES	% Population over 25 with less than 12 years of education	
QESL	% Population speaking English as a second language	
QEXTRCT	% Employment in extractive industries (fishing, farming, mining etc.)	
QFAM	% Children living in married couple families	
QFEMALE	% Female	
QFEMLBR	% Female participation in the labor force	
QFHH	% Families with female-headed households with no spouse present	
QHISP	% Hispanic population	
QMOHO	% Population living in mobile homes	
QNATAM	% Native American population	
QNOAUTO	% Housing units with no car available	
QPOVTY	% Persons living in poverty	
QRENTER	% Renter-occupied housing units	
QRICH200K	% Families earning more than $200,000 per year	
QSERV	% Employment in service occupations	
QSSBEN	% Households receiving Social Security benefits	
QUNOCCHU	% Unoccupied housing units	
QNRRES	% Population living in nursing facilities	2010 Census

Table 2
The social components retained from the principal components analysis.

Component	Cardinality	Name	Variance	Dominant Variables	Component Loading
1	–	Wealth	21.8	MHSEVAL	0.89
				PERCAP	0.87
				QRICH200K	0.79
				MDGRENT	0.76
				QED12LES	0.75
				QMOHO	−0.56
2	+	Age	13.0	QSSBEN	0.91
				QAGEDEP	0.86
				MEDAGE	0.83
				QFEMLBR	−0.74
3	+	Housing	11.7	QRENTER	0.75
				QNOAUTO	0.72
				QFAM	−0.68
				QBLACK	0.58
				QMOHO	−0.53
				PPUNIT	−0.52
4	+	Hispanic	7.3	QHISP	0.92
				QESL	0.92
5	+	Female	5.5	QFEMALE	0.73
				QNRRES	0.64
6	+	Native American	4.9	QNATAM	0.73
				QSERV	0.72
7	+	Asian	4.0	QASIAN	0.89

Table 3
The physical index variables and sources.

Variable	Source
Aspect	Derived from DEM
Biomass	USDA Forest Service
Elevation	USGS National Elevation Dataset
Hillshade	Derived from DEM
Forest Cover	Multi-Resolution Land Consortium
Precipitation	PRISM Climate Group
Population Density	US Census Bureau
Road Density	North Carolina Department of Transportation
Slope	Derived from DEM
Temperature	PRISM Climate Group

(Table A1). The results of the binomial regression and corresponding standardized coefficients were used to determine relative importance of each variable and magnitude of the relationship between variables (Table A2). The comparison values were then entered into extAhp20, an extension that produces criteria weights for each variable within ArcMap [46]. The output weighed road density the highest (16.40), followed by forest cover (16.13) and elevation (15.75) (Table A3). The consistency ratio of the AHP results was 0.04, aligning with the 0.1 threshold recommended by Saaty [47]. The results were mapped using the output capability in extAhp20. Zonal statistics was used to assign a mean physical vulnerability value to each tract.

Table 5
The reclassification criteria for the physical variables.

	Fuel	Topography	Climate	Development
High	+ Forest Cover + Biomass	+ Elevation + Slope - Aspect - Hillshade	- Temperature + Precipitation	- Population Density - Road Density
Low	- Forest Cover - Biomass	- Elevation - Slope + Aspect + Hillshade	+ Temperature - Precipitation	+ Population Density + Road Density

Table 6
The results of the multiple linear regressions between the physical variables and wildfire rates for all wildfires between 1985 and 2016.

Variable	Model #1 (AIC = 254.57, Adjusted R^2 = 0.20)			Model #2 (AIC = 248.25, Adjusted R^2 = 0.20)		
	Estimate	Z	p-value	Estimate	Z	p-value
Aspect	−0.016	−0.463	0.646	–	–	–
Biomass	−0.051	−2.034	0.048	–	–	–
Elevation	−0.006	−0.728	0.470	−0.005	−3.041	0.00
Forest Cover	0.250	2.851	0.007	0.217	3.962	0.00
Hillshade	−0.043	−0.543	0.590	–	–	–
Population Density	6.927	1.846	0.072	6.180	2.004	0.05
Precipitation	−0.002	−0.578	0.566	–	–	–
Road Density	−0.017	−0.375	0.710	–	–	–
Slope	0.056	0.268	0.790	–	–	–
Temperature	−0.449	−0.347	0.730	–	–	–

Wildfire rates were calculated by dividing the total acreage burned by the total acreage for each tract. To assess the risk factors for *large* wildfires, a multiple linear regression was performed between log-transformed wildfire rates for all wildfires between 1985 and 2016 and averages of the physical variables (Table 6). Zero values were removed to identify the physical variables specifically influencing wildfire size.

Following Emrich and Cutter [17] and Wigtil et al. [21], the intersection of social and physical vulnerability was illustrated using a bivariate mapping technique. To produce three classes, moderate-high and high classifications were combined to create the high classification and low and low-moderate classifications were combined to create the low classification.

4. Results

Following Cutter et al. [15], the social vulnerability scores were

Table 4
The results of the Kendall correlation and binomial regression between the physical variables and historical wildfires between 1985 and 2015. Model #1 includes all physical variables. Model #2 includes all significant variables.

	Kendall Correlation	Binomial Regressions							
Variable	tau	Model #1 (AIC = 145.62)				Model #2 (AIC = 136.74)			
		Coefficient	Standardized Coefficient	Z	p-value	Coefficient	Standardized Coefficient	Z	p-value
Aspect	−0.04.	0.017	0.274	0.757	0.449	–	–	–	–
Biomass	0.28**	−0.002	−0.068	−0.095	0.924	–	–	–	–
Elevation	0.14**	−0.007	−1.919	−1.399	0.162	−0.004	−1.195	−3.413	0.00
Forest Cover	0.37***	0.088	2.150	1.468	0.142	0.136	3.316	4.233	0.00
Hillshade	−0.33***	−0.107	−0.718	−1.784	0.074	−0.105	−0.703	−2.608	0.01
Population Density	−0.35***	0.212	0.224	0.080	0.936	–	–	–	–
Precipitation	0.25**	0.001	0.179	0.574	0.566	–	–	–	–
Road Density	−0.3sss3***	−0.052	−1.915	−1.700	0.089	−0.046	−1.716	−1.872	0.06
Slope	0.32***	0.198	1.055	1.174	0.241	–	–	–	–
Temperature	−0.12**	−0.199	−0.289	−0.232	0.816	–	–	–	–

***p < 0.001, **p < 0.01, *p < 0.05, . p < 0.1.

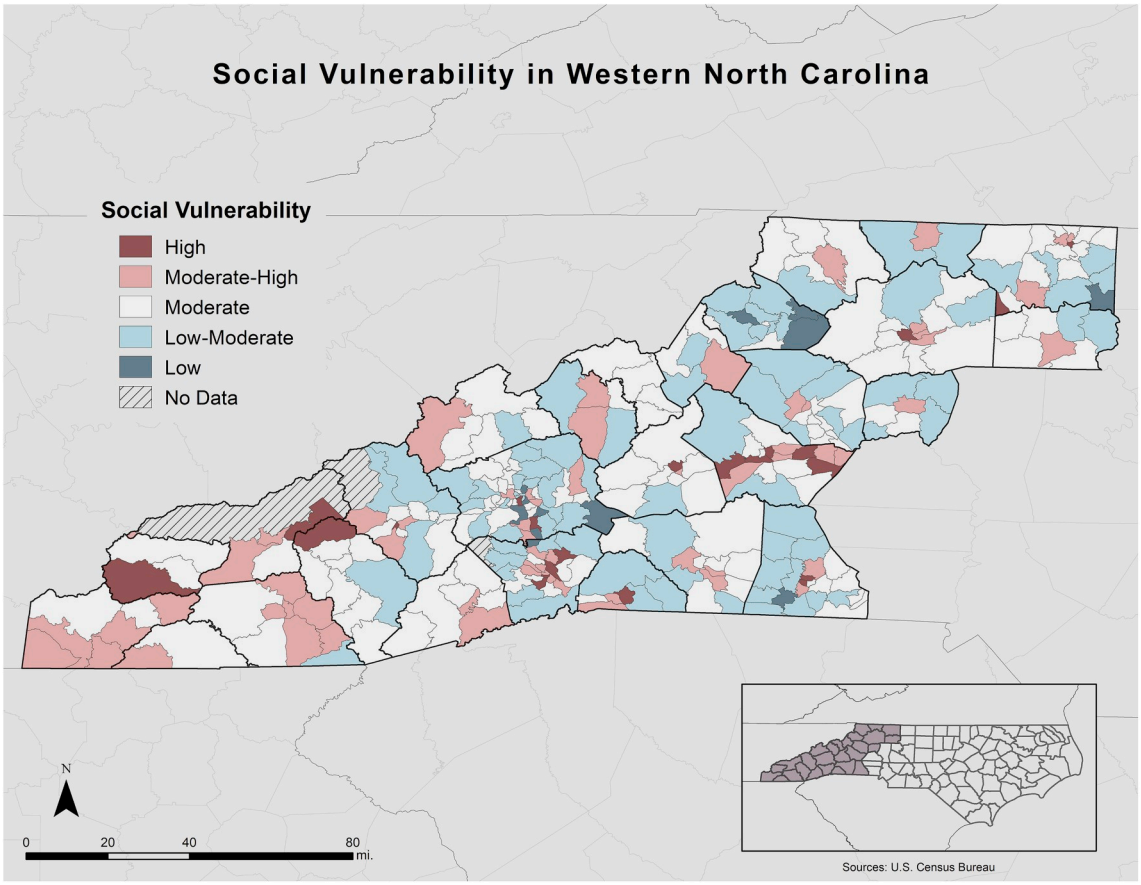

Fig. 2. Social vulnerability scores for western North Carolina, USA based on the social variables listed in Table 1.

mapped based on standard deviations from the mean into five classes ranging from < -1.5 to > 1.5 (Fig. 2). The five classes were labeled high, moderate-high, moderate, low-moderate, and low vulnerability using a methodology similar to Cutter et al. [15]. Of the 317 tracts, 23 (7%) were classified as high vulnerability, 62 (20%) as moderate-high, 134 (42%) as moderate, 86 (27%) as low-moderate, and 12 (4%) as low. The tract with the highest vulnerability was located in Henderson County, while the tract with the lowest vulnerability was located in Buncombe County. Graham County had the highest proportion of high vulnerability tracts with 1 out of 3 classified tracts (33%) classified as having high social vulnerability. Graham was followed by Burke County, where 5 out of 18 tracts (28%) were classified as having high social vulnerability. Watauga County had the highest proportion of low vulnerability tracts with 3 out of 13 (23%) classified as having low social vulnerability.

The mean physical vulnerability scores for each tract were also mapped based on standard deviations from the mean into five classes ranging from < -1.5 to > 1.5 (Fig. 3). Again, these five classes were labeled high, moderate-high, moderate, low-moderate, and low vulnerability. Of the 317 tracts, 19 (6%) were classified as high vulnerability, 89 (28%) as moderate-high, 110 (35%) as moderate, 74 (23%) as low-moderate, and 25 (8%) as low. The tract with the highest physical vulnerability was located in Haywood County, while the tract with the lowest physical vulnerability was located in Buncombe County. Macon County had the highest proportion of high vulnerability tracts with 4 out of 9 tracts (44%) classified as having high physical vulnerability. Buncombe County had the highest proportion of low vulnerability tracts with 13 out of 56 (23%) classified as having low physical vulnerability.

The 2016 wildfires were used to validate the physical index. The results of the correlation between mean physical vulnerability and 2016 wildfires rates in each tract indicated a significant correlation (rho = 0.36, p-value < 0.001). Additionally, the results of the binomial regression indicated that the physical vulnerability index was a significant predictor of the presence or absence of a 2016 wildfire ($\alpha = 0.001$).

A bivariate map was produced to illustrate the intersection of social and physical vulnerability (Fig. 4). The highest number of tracts (48) were classified as having moderate social and high physical vulnerability, followed by moderate social and moderate physical vulnerability (47). Swain County had the highest proportion of high vulnerability tracts with 3 out of the 4 classified tracts (75%) classified as having high social and physical vulnerability. Swain was followed by neighboring Macon County, where 5 out of 9 tracts (56%) were classified as having high social and physical vulnerability. Cleveland County had the highest proportion of low vulnerability tracts with 8 out of 22 (36%) of the tracts classified as having low social and physical vulnerability.

Similar to Lein and Stump [6], wildfire count, wildfire acreage, and average burned area (acreage burned /count) were compared to the combined vulnerability classifications. No wildfires occurred in tracts with low social and physical vulnerability. The majority of wildfires (166 of 178) were observed in tracts with high physical vulnerability. Additionally, the highest wildfire acreage burned occurred in tracts with moderate social and high physical vulnerability, suggesting the index is a reliable indicator of wildfire vulnerability in western North Carolina (Table 7).

5. Discussion

The objective of the study was to identify where social and physical wildlife vulnerability coincide in western North Carolina following the

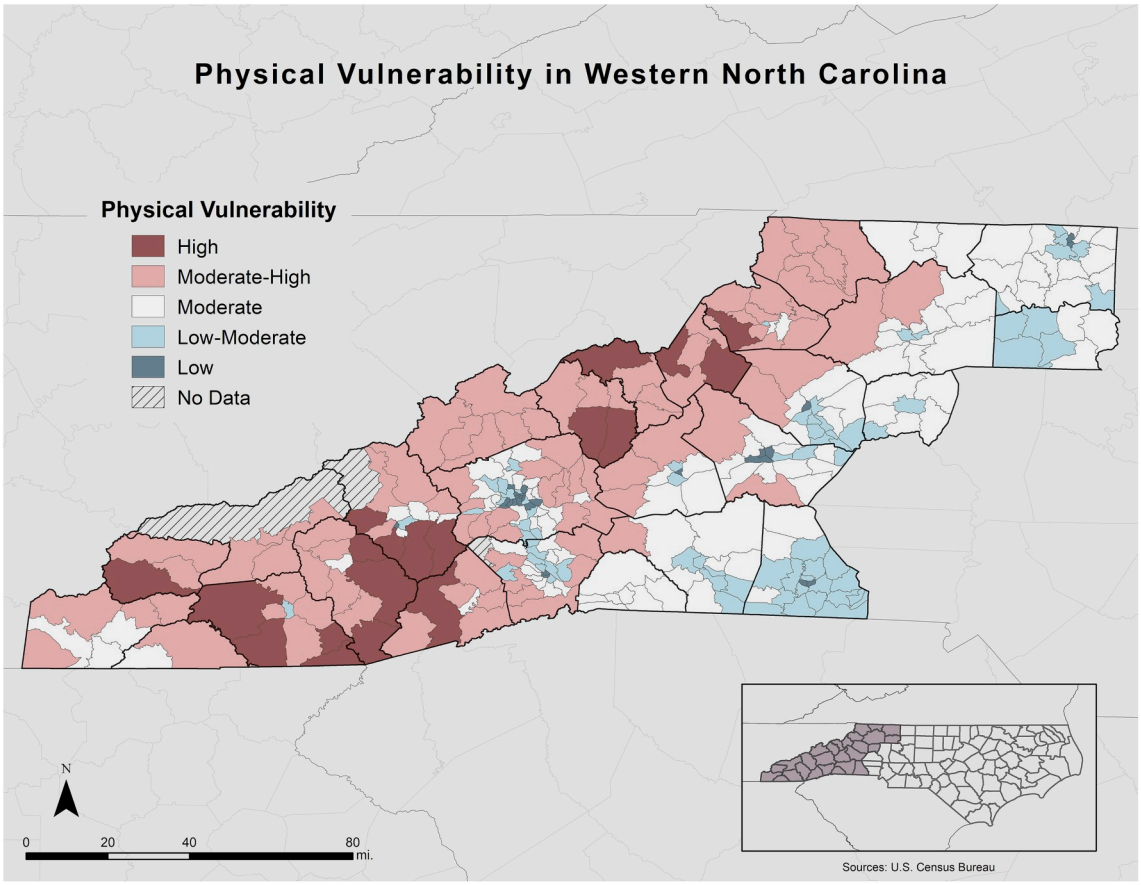

Fig. 3. Physical vulnerability scores for western North Carolina, USA based on the physical variables listed in Table 3.

unprecedented wildfires in 2016. The study fulfilled existing literature gaps by assessing vulnerability at the local scale, which can strengthen resilience in western North Carolina, an understudied region.

The methodology of Cutter et al. [15]'s SoVI, widely regarded as the foundational social vulnerability work, was followed to assess social vulnerability. The social vulnerability index revealed varying levels of social vulnerability throughout western North Carolina with elevated vulnerability in the southwestern portion of the region (Fig. 2). Individual component scores revealed social vulnerability to be driven by gender, employment, and race. Notably, the female component was comprised of two highly-correlated variables: percentage of the population that is female and percentage of the population living in nursing facilities, indicating an older - and thus, more vulnerable - female population in western North Carolina. The tract with highest social vulnerability, located in Henderson County, can be attributed to higher values for the Female, Hispanic, Age, and Native American components. In contrast, the tract with the lowest social vulnerability, located in Buncombe County, can be attributed to higher values for the Wealth component and lower values for the Native American component. Notably, in both cases, the Native American component was driven by population in the service industry. Graham and Burke counties had the highest proportion of social vulnerability. For both counties, higher vulnerability was attributed to large minority populations, similar to findings by Cutter et al. [15] and Cutter and Finch [13]. Graham County has a large Native American population, while Burke County has a large Asian population. Watauga County's low proportion of social vulnerability can be attributed to a higher amount of wealth compared to surrounding counties.

To determine physical vulnerability, the study embraced novel methods in GIS by informing the physical vulnerability index using historical wildfires (Table 4). Forest cover was the most significant positive predictor of wildfire. Forests provide fuels for wildfires, which is in contrast to developed locations with less flammable material. Additionally, invasive species in the region, such as the hemlock wooly adelgid, have led to the death of many trees, contributing additional fuels to wildfires. Similarly, biomass was positively correlated with wildfire, though it was not a significant predictor of wildfire presence due to multicollinearity with forest cover (Variance Inflation Factor = 3.9).

Both development variables, population and road density, were negatively associated with wildfire, indicating wildfires caused by human activity may often occur in rural locations instead of urban ones. Lein and Stump [6] also concluded that wildfires occurred most frequently in places with low population densities. These findings contradict other wildfire modeling studies, conducted outside of Appalachia, that identify road density (i.e., population factors) as a significant risk factor [4]. Both climate factors, precipitation and temperature, were not significant predictors of wildfire. Temperature's negative correlation with wildfires could be attributed to latitudinal changes, while precipitation's positive correlation with wildfires could be due to additional vegetation resulting from elevated precipitation. Similar to Maingi and Henry [7]; aspect had little influence on wildfires. The positive correlation between slope and wildfire was also consistent with findings from Maingi and Henry [7]. Steep slopes are drier and allow field upslope to be preheated before combustion [7]. This finding is in contrast to many existing wildfire modeling studies, which have found smaller slope gradients to increase wildfire occurrence [4]. However, the correlation between smaller slope gradients and increased wildfire occurrence often reflects the tendency of large populations to settle in locations with smoother terrain, which may not be the case in Appalachia [4].

Elevation was a significant negative indicator of wildfire, likely due

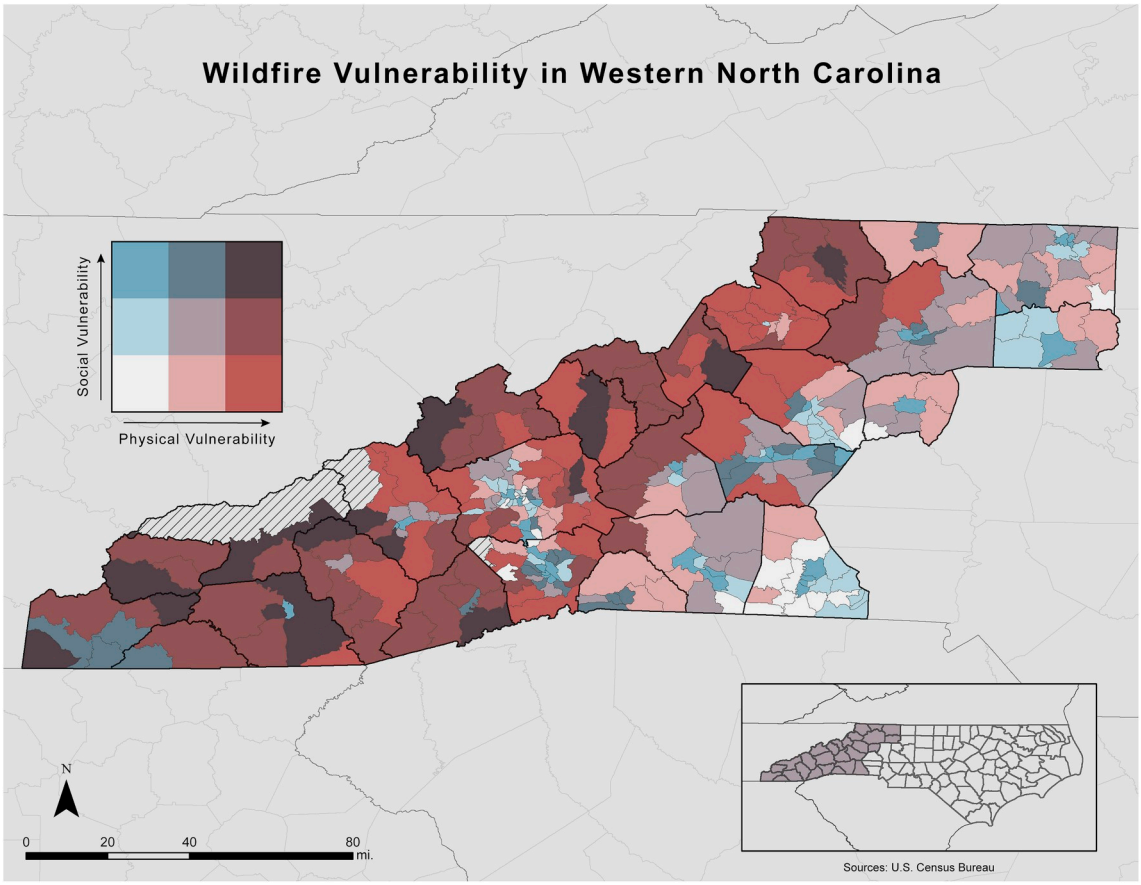

Fig. 4. Bivariate map depicting the intersection of social and physical wildfire vulnerability in western North Carolina, USA.

to lower moisture driving lower biomass at higher elevations. Flatley et al. [10] also noted this relationship in the Great Smoky Mountains National Park. Furthermore, Elevation is a significant predictor for wildfire worldwide with a meta-analysis of wildfire vulnerability models finding that many studies report elevation as one of the most significant and relevant variables for modeling [4]. Specifically, lower (rather than higher) elevations, such as those in Appalachia, increased human-caused fire occurrence in countries ranging from Southern Europe, South Korea, the Middle East, and the western United States [48–52].

The physical vulnerability index revealed increasing physical vulnerability moving southward, toward the Great Smoky Mountains National Park, and westward, toward Appalachia (Fig. 3). The results of the regressions indicate that decreasing development combined with increasing forest cover is likely driving this trend instead of increasing elevation. The tract with the highest physical vulnerability was in Haywood County. The tract neighbors the Great Smoky Mountains National Park and the Eastern Cherokee Reservation and includes a segment of the Blue Ridge Parkway. At the county level, Macon County had the highest proportion of physical wildfire vulnerability, likely due to the Nantahala National Forest. This indicates that urban areas located near national forests, such as Maggie Valley in Haywood and Franklin in Macon, are particularly at risk. The tract with the lowest physical vulnerability was in the center of the City of Asheville in Buncombe County, where population and road densities are high and forest cover is low. Buncombe was also the county with the lowest proportion of physical vulnerability.

To determine which physical characteristics increase wildfire acreage, a multiple linear regression was run between physical variables and rates for all wildfires between 1985 and 2016 (Table 6). For all wildfires between 1985 and 2016, forest cover and population density were positive predictors and elevation was a negative predictor

Table 7
The combined vulnerability classifications and wildfire count, acreage, and average burned area for all wildfires, 2016 wildfires, and 1985–2015 wildfires.

Class	Tracts in Class	All Wildfires			2016			1985–2015		
		Count	Acreage	Average	Count	Acreage	Average	Count	Acreage	Average
Low Social - Low Physical	22 (7%)	0	0	0	0	0	0	0	0	0
Moderate Social - Low Physical	39 (12%)	0	0	0	0	0	0	0	0	0
High Social - Low Physical	38 (12%)	1	132	132	0	0	0	1	132	132
Low Social - Moderate Physical	37 (12%)	4	2297	574	1	0.3	0.3	3	2297	766
Moderate Social - Moderate Physical	47 (15%)	4	6580	1645	0	0	0	4	6580	1645
High Social - Moderate Physical	26 (8%)	3	2685	895	0	0	0	3	2685	895
Low Social - High Physical	39 (12%)	43	34,275	797	13	10,037	772	30	24,237	808
Moderate Social - High Physical	48 (12%)	98	81,834	835	39	51,943	1332	59	29,891	507
High Social - High Physical	21 (7%)	25	20,752	830	15	12,667	845	10	8085	809

of wildfire rates. Forest cover was the most significant predictor, likely because forests present more fuels for wildfire growth. In contrast to the results of the binary regression, population density's positive direction indicates that human presence may increase the likelihood of *large* wildfires, demonstrating the potential risks of settlement in the WUI. The negative direction of elevation, consistent with the results of the binary regression, indicates that higher elevations decrease the likelihood of large wildfires.

Overall wildfire vulnerability was greatest in the southwest, consistent with Wigtil et al. [21] (Fig. 4). Swain and Macon counties had the highest overall vulnerability likely due to a large number of protected lands and rural communities. Cleveland County had the lowest overall vulnerability likely due to its eastward location and the presence of three urban areas: Shelby, Gastonia, and Boiling Springs. Notably, Buncombe County, home to Asheville, and Henderson County, home to the Town of Hendersonville, demonstrated vulnerability patterns that differed from the rest of western North Carolina, but for different reasons. Both locations had low physical vulnerability in comparison to the surrounding region; however, Buncombe had lower social vulnerability than Henderson. Though no wildfires occurred in the Asheville or Hendersonville limits between 1985 and 2016, the 2016 8000-acre Party Rock fire occurred in moderate-high physical vulnerability tracts less than ten miles from both locations, demonstrating the variability in the region, as well as the risks of settling in the WUI.

Validation revealed a high number of wildfires in tracts classified as highly physically vulnerable, indicating the index accurately predicted wildfire presence (Table 7). The outcome demonstrates how past events can be used to inform policies to enhance resilience to future events. Overall, tracts with lower social vulnerability had smaller wildfires. Communities with low social vulnerability may have more resources to mitigate wildfires, whereas communities with greater vulnerability may have fewer resources to prevent wildfires, causing wildfires to be most devastating in communities who are less equipped for recovery. There were several notable outliers to the trend of increasing wildfires with increasing vulnerability. For all wildfires, the moderate physical and social vulnerability category experienced four wildfires with a large average size of 1644 acres. The large average size is driven primarily by the 1985 4610-acre, High Peak fire in Burke County. The fire occurred during extremely dry conditions and was the worst fire in the county's history [53]. For the 2016 wildfires, the high physical and moderate social vulnerability category experienced 39 wildfires with a large average size of 1332 acres. Most of the largest 2016 wildfires, including the 14,092-acre Tellico fire, 11,757-acre Rock Mountain fire, 9238-acre Boteler fire, 8453-acre Maple Springs fire, and 7930-acre Party Rock fire, occurred in tracts with high physical and moderate social vulnerability. Despite these outliers, the results of the validation demonstrate the potential utility of indices for successfully pinpointing vulnerability and informing policymaking.

6. Conclusion

The results of the individual and combined indices revealed high vulnerability in western North Carolina, though the nature of the vulnerability varied throughout the region. In contrast, previous studies have indicated low vulnerability to natural hazards in western North Carolina compared to eastern North Carolina and the U.S. (e.g., Refs. [15,17,21]). Additionally, substantial drivers of wildfire vary globally [48–52]. These differences highlight the importance of evaluating vulnerability at a local scale. Future studies using similar methods should consider adding index variables that reflect the fire regime of the study area.

Though validation provides a method for assessing accuracy, there are inherent limitations associated with modeling real-world vulnerability using indices. It is unlikely the index captured all of the variables contributing to wildfire vulnerability. Additionally, the index did not account for external influences that may enhance resilience to natural hazards, such as community relationships. The social index was subject to uncertainties due to the margins of error associated with socioeconomic data. Furthermore, the social index captures modern social vulnerability. It is likely that social vulnerability has changed between 1985 and 2016, the temporal range of the events in this study. All wildfires may not have been recorded in the dataset used for this study. The physical index could be strengthened by integrating additional historical fire data, as well as information about prescribed burns. Though the study was conducted at a more local scale than previous studies, future analyses could be strengthened by assessing vulnerability at an even smaller scale, such as the neighborhood level. Finally, economic and health data could provide an additional validation to the overall vulnerability index.

This study contributes to ongoing work by the USDA Forest Service to assess wildfire hazard in the U.S. As severe events become more likely, future analyses should evaluate local resilience to natural hazards, particularly drought and wildfires, in western North Carolina. Additionally, future analyses should consider the health impacts of exposure to smoke from large wildfire outbreaks like the event in 2016. Given the widespread variability of social vulnerability throughout the region, vulnerability to other natural hazards should be explored.

The results of the index reveal that impacts of future wildfires on quality of life will vary across the region. Therefore, targeted responses are needed. With the inclusion of socioeconomic characteristics in the wildfire vulnerability index, policymakers can pinpoint specific communities and develop personalized policies to increase resilience. By providing transparency to the public, the results of the index empower vulnerable communities to take action to mitigate the impacts of unprecedented outbreaks like the one in 2016.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2019.101123.

Appendix A

Table A1
The equal interval reclassifications of the physical variables for the physical vulnerability index.

Variable	Unit	Reclassified Value				
		1 (Low Risk)	2	3	4	5 (High Risk)
Aspect	°	288.0–360.0	216.0–288.0	144.0–216.0	72.0–144.0	0–72.0
Biomass	Mg/ha	−30.2–78.9	78.9–188.0	188.0–297.1	297.1–406.2	406.2–515.3
Elevation	ft	172.5–544.1	544.1–915.7	915.7–1287.3	1287.3–1658.9	1658.9–2030.5
Forest	%	0–19.8	19.8–39.6	39.6–59.3	59.3–79.1	79.1–98.9
Hillshade	°	203.2–254.0	152.4–203.2	101.6–152.4	50.8–101.6	0–50.8
Population	Persons/Acre	6.4–7.9	4.8–6.4	3.2–4.8	1.6–3.2	0–1.6
Precipitation	mm	925.0–1248.0	1248.0–1571.0	1571.0–1893.9	1893.9–2216.9	2216.9–2539.9
Road	Roads/Acre	196.6–245.6	147.7–196.6	98.7–147.7	49.7–98.7	0.80–49.7
Slope	°	0–15.0	15.0–30.0	30.0–45.0	45.0–60.0	60.0–75.0
Temperature	°C	14.1–15.7	12.5–14.1	10.9–12.5	9.3–10.9	7.7–9.3

Table A2
The input parameters for the analytical hierarchy process.

	Aspect	Biomass	Elevation	Forest	Hillshade	Population	Precipitation	Road	Slope	Temperature
Aspect	1	1	1/2	1/2	1	1	1	1/2	1	1
Biomass	1	1	1/8	1/9	1/3	1	1	1/8	1/4	1
Elevation	2	8	1	1	1	3	3	1	1	2
Forest	2	9	1	1	1	3	3	1	1	2
Hillshade	1	3	1	1	1	1	1	1	1	1
Population	1	1	1/9	1/3	1	1	1	1/3	1	1
Precipitation	1	1	1/2	1/3	1	1	1	1/3	1/2	1
Road	2	8	1	1	1	3	3	1	1	3
Slope	1	4	1	1	1	1	2	1	1	1
Temperature	1	1	1/2	1/2	1	1	1	1/3	1	1

Table A3
The physical variable weightings produced by the analytical hierarchy process.

Variable	Weight
Aspect	7.2
Biomass	4.0
Elevation	15.8
Forest	16.1
Hillshade	10.2
Population	6.4
Precipitation	5.9
Road	16.4
Slope	11.1
Temperature	6.9

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