AN ASSESSMENT OF WILDFIRE VULNERABILITY IN
WESTERN NORTH CAROLINA, USA FOLLOWING THE 2016 WILDFIRES

A Thesis
by
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Abstract

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WESTERN NORTH CAROLINA, USA FOLLOWING THE 2016 WILDFIRES

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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 socioeconomic and physical data in a geographic information system, specific locations of vulnerability were identified and validated using wildfire perimeters from 2016. The study contributes to vulnerability research by embracing novel techniques through the use of validation. The vulnerability index indicates that social vulnerability varies greatly across 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, as well as enables policymakers to identify opportunities to prepare for resilience by targeting vulnerability hotspots.

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I would like to recognize the U.S. Census Bureau, U.S. Geological Survey, and U.S. Forest Service for providing the data necessary to complete this study. I thank Appalachian State's Research Institute for Environment, Energy, and Economics for providing research funding and the Appalachian State College of Arts and Sciences, the Appalachian State Office of Student Research, and Gamma Theta Upsilon for enabling me to present the culmination of my research at the Association of American Geographers Annual Meeting.

Though I look forward to the future, it will be bittersweet to walk across the stage in May. I am overwhelmed by the opportunities provided to me during my past five years at Appalachian State. I am especially fortunate to have found my home in the Department of Geography & Planning, where I had the opportunity to get to know many of the wonderful faculty members on a personal level. I am deeply indebted to Dr. Jessica Mitchell, who encouraged me to become involved with research as a sophomore and invested her valuable

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Foreword

The main body of this thesis is formatted to the guidelines for manuscript submission to *Natural Hazards*, an official journal of the International Society for the Prevention and Mitigation of Natural Hazards.

Introduction

  In late 2016, large-scale wildfires occurred throughout Southern Appalachia following a severe drought throughout the southeastern U.S. The wildfires, resembling fires in the western portion of the country by burning into canopies, roots, and riparian areas, were unprecedented for Appalachia. From late October through early December 2016, approximately 75,000 acres burned in western North Carolina. Western North Carolina's economy is reliant on the agricultural and tourism sectors, thus wildfires have the capacity to severely impact local communities. In the future, projected temperature increases and precipitation variability could further stress water resources in the region, causing more frequent and intense drought and wildfire events (IPCC 2012). 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.

  A wildfire is "any nonstructure fire, other than prescribed fire, that occurs in the wildland" (USFS 2018a). While fire-dependent ecosystems rely on fire, fire-sensitive ecosystems rely on fire suppression. Suppression has increased the density of vegetation and fire-sensitive species, which contribute to elevated wildfire intensity (Aldrich et al. 2014). Throughout the past few decades, increases in season length, fire size, acreage burned, and extreme behavior have complicated fire management (USFS 2018c). At the same time, individuals have settled into the zone where vegetation meets development, called the wildland-urban interface (WUI), further enhancing vulnerability.

  Previous studies have explored the drivers of wildfire vulnerability. Human development, including population and road densities, affect the likelihood of wildfire

occurrence (Feltman et al. 2012; Lein and Stump 2009; Maingi and Henry 2007; Munn et al. 2003). The complex climate and topography of mountainous regions also influences wildfire. Dry conditions and locations elevate wildfire frequency and intensity (Aldrich et al. 2014; Flatley et al. 2011; Lafon et al. 2005). Topographic characteristics, such as elevation, slope, aspect, illumination, and fuels, also affect wildfire behavior (Flatley et al. 2011; Maingi and Henry 2007; Lein and Stump 2009). Socially, variables relating to economic status and educational attainment have been demonstrated to influence wildfire occurrence (Feltman et al. 2012; Gaither et al. 2011).

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. The objective of this study was to identify locations vulnerable to wildfire in western North Carolina, an understudied region. To determine vulnerable locations, data was obtained from a variety of sources, including the U.S. Census Bureau, U.S. Geological Survey, and U.S. Forest Service. Indices were produced using multi-criteria decision making in a GIS. A social vulnerability index was produced following Dr. Susan Cutter's Social Vulnerability Index (SoVI). To evaluate physical vulnerability, a Kendall correlation and binomial regression were used to evaluate the physical variables influencing historical wildfires and inform an analytical hierarchy process. Using this information, a physical vulnerability index was produced and validated using wildfire perimeters from 2016. The physical drivers of wildfire size were then identified using a multiple linear regression. A bivariate mapping technique was employed to determine the intersection of social and physical wildfire vulnerability.

This study embraced novel methods to explore wildfire vulnerability. Socially, gender, employment, and race influenced vulnerability the most. Physically, forest cover, road density, elevation, and illumination were significant predictors of wildfire presence, while forest cover, population density, and elevation were significant predictors of wildfire size. While social and physical vulnerability was variable across the region, the results revealed the highest wildfire vulnerability to be in the southwestern portion of the region, near the Great Smoky Mountains National Park. The rural, mountainous locations most vulnerable to wildfire are also the least equipped for mitigation. Because vulnerability varies across the region, targeted responses are needed. The results demonstrate the potential utility of indices for accurately assessing vulnerability to hazards. The wildfire vulnerability index empowers communities, informs policymakers, and provides a novel methodology for assessing wildfire vulnerability in a previously understudied region.

An Assessment 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. 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 socioeconomic and physical data in a geographic information system, specific locations of vulnerability were identified and validated using wildfire perimeters from 2016. The study contributes to vulnerability research by embracing novel techniques through the use of validation. 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, as well as enables policymakers to identify opportunities to prepare for resilience by targeting vulnerability hotspots.

1. **Introduction**

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, accumulating fuel loads, and arson (Margulis 2016). 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 (Chavez 2016). 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 zone where vegetation meets development, called the wildland-urban interface (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 (Mattise and Foreman 2016). 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 (IPCC 2012). 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.

2. Literature Synthesis

2.1. Wildfire in Appalachia

A wildfire is "any nonstructure fire, other than prescribed fire, that occurs in the wildland" (USFS 2018a). While fire-dependent ecosystems rely on fire, fire-sensitive ecosystems rely on fire suppression. 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 (Aldrich et al. 2014). Throughout the past few decades, wildfire management has changed due to increases in season length, fire size, acreage burned, and extreme behavior (USFS 2018c).

Though wildfires are beneficial to forest ecosystems, it threatens communities in the WUI. 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 (Feltman et al. 2012; Lein and Stump 2009; Maingi and Henry 2007; Munn et al. 2003). Additionally, wildfires resulting from human activities burn more area and occur more often compared to naturally-caused wildfires (Lafon et al. 2005).

The complex climate and topography of mountainous regions influences wildfire. Dry conditions and locations elevate wildfire frequency and intensity (e.g., Aldrich et al. 2014; Flatley et al. 2011; Lafon et al. 2005). Lafon et al. (2005) 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 (2007) 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. 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. 2011). Flatley et al. (2011) 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 (2007) determined that fire occurrence was highest at higher elevations and on steeper slopes in eastern Kentucky. Lein and Stump (2009) 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.

2.2. 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 (Gallopín 2006). Vulnerability varies spatiotemporally, making it geographical in nature (Cutter and Finch 2008). Vulnerability

can be a result of biophysical risks, social responses, or hazards of place (Cutter 1996). Cutter (1996)'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. (2003)'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 (Cutter and Emrich 2017). The SoVI has been widely used to study exposure to hazards, including drought, flooding, and sea level rise, both nationally and internationally (e.g., Emrich and Cutter 2011; Guillard-Gonçalves et al. 2015; Siagian et al. 2014). 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. Wigtil et al. (2016) created a wildfire vulnerability index 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. (2012) 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. (2011) 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. Cutter et al. (2003) 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., Cutter et al. 2003; Cutter and Finch 2008, Emrich and Cutter 2011) and emphasize the importance of examining vulnerability at a local scale (e.g., Cutter 1996). The SoVI is a comparative metric, so results vary based on the size and characteristics of the study area (Cutter and Emrich 2017). Sub-county level evaluation of vulnerability facilitates more effective policymaking by pinpointing local vulnerabilities, which is particularly valuable in complex regions like Appalachia.

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 (Ager et al. 2015). 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. 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. 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.

3. Study Area

The study focuses on census tracts in the 27 counties of western North Carolina, USA. Approximately 75,000 acres of these counties burned from late October through early December 2016. Western North Carolina is an understudied region in wildfire literature, despite being particularly impacted by the event in 2016. Western North Carolina 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 (NEMAC 2012). For example, precipitation ranges from less than 40 inches annually in Buncombe County to more than 100 inches in the neighboring Transylvania County (PRISM Climate Group 2018).

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) (USCB 2016a). Additionally, 23 of the 27 counties have a rural population greater than 50% (USCB 2010). 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).

4. Methods

In the present study, GIS is employed for multi-criteria decision-making (MCDM), which is the process of combining information from several criteria to form a single index of evaluation (Chen et al. 2010). MCDM requires the creator to make decisions about a variety of factors, including variables, scales, and weights, and these decisions introduce subjectivity to indices (Tate 2012). Fortunately, GIS-based methods exist for informing and validating these decisions, making indices more reliable tools for decision-makers.

4.1. Social Vulnerability

Socioeconomic data was downloaded from the 2010 Census and 2012-6 American Community Survey for 317 census tracts in western North Carolina. Three tracts were excluded from the analysis due to lack of population and thus data availability. The variables chosen followed Cutter and Emrich (2017) who identified the 27 variables as proxies for characteristics known to influence hazards vulnerability (Table 1).

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 (Kaiser 1960) (Table 2). The directionality of the wealth component was reversed because a higher amount of wealth indicates lower vulnerability. In ArcMap 10.4.1, the components were joined to the tracts and summed to produce the social vulnerability index.

4.2. 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 (Homer et al. 2015). 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 (Moisen et al. 2008). 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 (USGS 2018b). Linear aspect values were computed using the Geomorphometry and Gradient Metrics Toolbox 2.0 (Evans et al. 2014). From the PRISM Climate Group, 30-year normals for precipitation and temperature were downloaded (PRISM Climate Group 2018). Finally, humans influence wildfire by developing in the WUI. Population density was calculated based on population data from the U.S. Census Bureau (USCB) (2016b). Road density was calculated using a shapefile of statewide system and non-system road routes acquired from the North Carolina Department of Transportation (NCDOT) (2017) (Table 3).

The subjectivity of weighting decisions can be reduced using methods in GIS, such as the analytical hierarchy process (AHP). AHP is a theory of measurement through pairwise comparisons that relies on the judgements of experts to derive priority scales (Saaty 2008). 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 (Chen et al. 2010). Previous studies have demonstrated the value of AHP for strengthening natural hazards MCDM, including wildfire risk (Vadrevu et al. 2010).

To determine weighting and enable validation of vulnerable locations, 2016 wildfires perimeters were obtained from the Geospatial Multi-Agency Coordination (GeoMAC) (USGS 2018a) and 1985-2015 (historical) wildfire perimeters were obtained from the USDA Forest Service (USFS 2018b). 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 (R Core Team 2017), 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, followed by illumination (hillshade) (Table 4).

Similar to Yalcin et al. (2011), 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 (Table 8). 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 9). The comparison values were then entered into extAhp20, an extension that produces criteria weights for each variable (Marinoni 2004). The output weighed road density the highest (16.40), followed by forest cover (16.13) and elevation (15.75) (Table 10). The consistency ratio of the AHP results was 0.04, aligning with the 0.1 threshold recommended by Saaty (1980). The results were mapped using the output capability in

extAhp20. Zonal statistics was used to assign a mean physical vulnerability value to each tract.

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 (2011) and Wigtil et al. (2016), 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.

5. Results

Following Cutter et al. (2003), the social vulnerability scores were mapped based on standard deviations from the mean into five classes ranging from < 1.5 to > 1.5 (Fig. 2). 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). 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 (2009), 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).

6. Discussion

The objective of the study was to identify where social and physical wildlife vulnerability coincide in western North Carolina following the 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. (2003)'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. (2003) and Cutter and Finch (2008). Graham County has a large Native American population, while Burke County has a large Asian population. Watauga County's low

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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 (2009) also concluded that wildfires occurred most frequently in places with low population densities. 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 (2007), aspect had little influence on wildfires. The positive correlation between slope and wildfire was also consistent with findings from Maingi and Henry (2007). Steep slopes are drier and allow field upslope to be preheated before combustion (Maingi and Henry 2007). Finally, elevation was a significant negative indicator of wildfire, likely due to lower moisture driving lower biomass at higher elevations. Flatley et al. (2011) also noted this relationship in the Great Smoky Mountains National Park.

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 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 larger wildfires.

Overall wildfire vulnerability was greatest in the southwest, consistent with Wigtil et al. (2016) (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 8,000-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 1,644 acres. The large

average size is driven primarily by the 1985 4,610-acre, High Peak fire in Burke County. The fire occurred during extremely dry conditions and was the worst fire in the county's history (Flanagan 2015). For the 2016 wildfires, the high physical and moderate social vulnerability category experienced 39 wildfires with a large average size of 1,332 acres. Most of the largest 2016 wildfires, including the 14,092-acre Tellico fire, 11,757-acre Rock Mountain fire, 9,238-acre Boteler fire, 8,453-acre Maple Springs fire, and 7,930-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.

7. 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., Cutter et al. 2003; Emrich and Cutter 2011; Wigtil et al. 2016). These differences highlight the importance of evaluating vulnerability at a local scale.

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. The physical index could be strengthened with 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 block group 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.

Acknowledgments

References

Ager AA, Kline JD, Fischer AP (2015) Coupling the biophysical and social dimensions of wildfire risk to improve wildfire mitigation planning. Risk Anal 35:1393–1406. https://doi.org/10.1111/risa.12373

Aldrich SR, Lafon CW, Grissino-Mayer HD, DeWeese GG (2014) Fire history and its relations with land use and climate over three centuries in the Central Appalachian Mountains, USA. J Biogeogr 41:2093–2104. https://doi.org/10.1111/jbi.12373

Chavez K. (2016) Outbreak of WNC Wildfires Takes Toll on Wildfire, Environment. Citizen Times. http://www.citizen-times.com/story/news/local/2016/11/18/outbreak-wnc-wildfires-takes-toll-wildlife-environment/93788956/. Accessed 18 Apr 2018.

Chen Y, Yu J, Khan S (2010) Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. Environ Model Softw 25:1582–1591. https://doi.org/10.1016/j.envsoft.2010.06.001

Cutter SL (1996) Vulnerability to hazards. Prog Hum Geogr 20:529–539. https://doi.org/10.1177/030913259602000407

Cutter SL, Boruff BJ, Shirley WL (2003) Social vulnerability to environmental hazards. Soc Sci Q 84:242–261. https://doi.org/10.1111/1540-6237.8402002

Cutter SL, Emrich CT (2017) Social Vulnerability Index (SoVI®): Methodology and Limitations. Federal Emergency Management Agency (FEMA). https://data.femadata.com/FIMA/NHRAP/NationalRiskIndex/FinalDocumentation/Social%20Vulnerability%20-%20SoVI/Social%20Vulnerability%20Index%20Primer.pdf. Accessed 18 Apr 2018.

Cutter SL, Finch C (2008) Temporal and spatial changes in social vulnerability to natural

hazards. Proc Natl Acad Sci U S A 105:2301–2306.

https://doi.org/10.1073/pnas.0710375105

Emrich CT, Cutter SL (2011) Social vulnerability to climate-sensitive hazards in the

Southern United States Weather Clim Soc 3:193–208.

https://doi.org/10.1175/2011WCAS1092.1

Evans JS, Oakleaf J, Cushman SS, Theobald D (2014) An ArcGIS Toolbox for Surface

Gradient and Geomorphometric Modeling, version 2.0-0.

http://evansmurphy.wix.com/evansspatial. Accessed 18 Apr 2018.

Feltman JA, Straka TJ, Post CJ, Sperry SL (2012) Geospatial analysis application to forecast

wildfire occurrences in South Carolina. Forests 3:265–282.

https://doi.org/10.3390/f3020265

Flanagan GL (2015) Remembering the worst wildfire in Burke County's history.

http://www.morganton.com/news/remembering-the-worst-wildfire-in-burke-county-s-

history/article_04427898-da5b-11e4-89f9-8b7375fb2e99.html. Accessed 18 Apr

2018.

Flatley WT, Lafon CW, Grissino-Mayer HD (2011) Climatic and topographic controls on

patterns of fire in the Southern and Central Appalachian Mountains, USA. Landsc

Ecol 26:195–209. https://doi.org/10.1007/s10980-010-9553-3

Gaither CJ, Poudyal NC, Goodrick S, Bowker JM, Malone S, Gan J (2011) Wildland fire risk

and social vulnerability in the Southeastern United States: An exploratory spatial data

analysis approach. For Policy Econ 13:24–36.

https://doi.org/10.1016/j.forpol.2010.07.009

Gallopín GC (2006) Linkages between vulnerability, resilience, and adaptive capacity. Glob Environ Chang 16:293–303. https://doi.org/10.1016/j.gloenvcha.2006.02.004

Guillard-Gonçalves C, Cutter SL, Emrich CT, Zêzere JL (2015) Application of Social Vulnerability Index (SoVI) and delineation of natural risk zones in Greater Lisbon, Portugal. J Risk Res 18:651–674. https://doi.org/10.1080/13669877.2014.910689

Homer C, Dewitz J, Yang L, Jin S, Danielson P, Xian G, Coulston J, Herold N, Wickham J, Megown K (2015) Completion of the 2011 National Land Cover Database for the conterminous United States - representing a decade of land cover change information. Photogramm Eng Remote Sensing 345–354. https://doi.org/DOI: 10.14358/PERS.81.5.345

IPCC (2012) Managing the risks of extreme events and disasters to advance climate change adaptation. Cambridge University Press, Cambridge, United Kingdom, and New York, New York, USA

Kaiser HF (1960) The application of electronic computers to factor analysis. Educ Psychol Meas 20: 141-151. https://doi.org/10.1177/001316446002000116

Lafon C, Grissino-Mayer H (2007) Spatial patterns of fire occurrence in the Central Appalachian Mountains and implications for wildland fire management. Phys Geogr 28:1–20. https://doi.org/10.2747/0272-3646.28.1.1

Lafon C, Hoss J, Grissino-Mayer H (2005) The contemporary fire regime of the Central Appalachian Mountains and its relation to climate. Phys Geogr 26:126–146. https://doi.org/10.2747/0272-3646.26.2.126

Lein JK, Stump NI (2009) Assessing wildfire potential within the wildland-urban interface:
A southeastern Ohio example. Appl Geogr 29:21–34.
https://doi.org/10.1016/j.apgeog.2008.06.002

Maingi JK, Henry MC (2007) Factors influencing wildfire occurrence and distribution in
eastern Kentucky, USA. Int J Wildl Fire 16:23–33. https://doi.org/10.1071/WF06007

Margulis A (2016) WNC Wildfire Season Unprecedented, No End In Sight. Citizen Times.
https://www.citizen-times.com/story/news/local/2016/11/17/wnc-wildfire-season-
unprecedented-no-end-sight/94013160/. Accessed 18 Apr 2018.

Mattise J, Foreman T (2016) Amid wildfires, North Carolina getaway turns to ghost town.
Associated Press (AP) News.
https://apnews.com/726e8c645c094e9eb59d07027fd2eeaf. Accessed 18 Apr 2018.

Marinoni O (2004) Implementation of the analytical hierarchy process with VBA in ArcGIS.
Comput Geosci 30:637-646. https://doi.org/10.1016/j.cageo.2004.03.010

Moisen GG, Blackard JA, Finco MV, Helmer EH, Holden GR, Hoppus ML, Jacobs DM,
Lister AJ, Nelson MD, Riemann R, Ruefenacht B, Salajanu D, Weyermann DL,
Winterberger KC, Brandeis TJ, Czaplewski RL, McRoberts RE, Patterson PL,
Tymcio RP (2008) Mapping U.S. forest biomass using nationwide forest inventory
data and moderate resolution information. Remote Sens Environ 112:1658-1677.
https://doi.org/10.1016/j.rse.2007.08.021

Munn I, Zhai YS, Evans DL (2003) Modeling forest fire probabilities in the South Central
United States using FIA data. South J Appl For 27: 11-17.
https://doi.org/10.1093/sjaf/27.1.11

National Environmental Modeling and Analysis Center (NEMAC) (2012) Western North

Carolina Vitality Index. http://www.wncvitalityindex.org/. Accessed 18 Apr 2018.

North Carolina Department of Transportation (NCDOT) (2017) GIS Data Layers: Statewide

System & Non-System Road Routes.

https://connect.ncdot.gov/resources/gis/pages/gis-data-layers.aspx. Accessed 18 Apr

2018.

PRISM Climate Group (2018) 30-Year Normals. http://prism.oregonstate.edu. Accessed 18

Apr 2018.

R Core Team (2017) R: A language and environment for statistical computing. R Foundation

for Statistical Computing. http://www.R-project.org/. Accessed 18 Apr 2018.

Saaty TL (2008) Decision making with the analytic hierarchy process. Int J Services Sciences

1:83-98. https://doi.org/10.1504/IJSSci.2008.01759

Saaty TL (1980) The Analytic Hierarchy Process. McGraw-Hill, New York

Siagian TH, Purhadi P, Suhartono S, Ritonga H (2014). Social vulnerability to natural

hazards in Indonesia: Driving factors and policy implications. Nat Hazards 70:1603–

1617. https://doi.org/10.1007/s11069-013-0888-3

Tate E (2012) Social vulnerability indices: A comparative assessment using uncertainty and

sensitivity analysis. Nat Hazards 63:325–347. https://doi.org/10.1007/s11069-012-

0152-2

U.S. Census Bureau (USCB) (2010) Urban and rural, 2010 Census.

https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DE

C_10_SF1_H2&prodType=table. Accessed 18 Apr 2018.

U.S. Census Bureau (USCB) (2016a) Median household income in the past 12 months (in

    2016 inflation-adjusted dollars), 2012-2016 American Community Survey estimates.

    https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=AC

    S_16_5YR_B19013&prodType=table. Accessed 18 Apr 2018.

U.S. Census Bureau (USCB) (2016b) Total population, 2012-2016 American Community

    Survey estimates.

    https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=AC

    S_16_5YR_B01003&prodType=table. Accessed 18 Apr 2018.

U.S. Forest Service (USFS) (2018a) Fire Terminology.

    https://www.fs.fed.us/nwacfire/home/terminology.html. Accessed 18 Apr 2018.

U.S. Forest Service (USFS) (2018b) FSGeodata Clearinghouse.

    https://data.fs.usda.gov/geodata/. Accessed 18 Apr 2018.

U.S. Forest Service (USFS) (2018c) Wildland Fire. https://www.fs.fed.us/managing-

    land/fire. Accessed 18 Apr 2018.

U.S. Geological Survey (USGS) (2018a) Geospatial Multi-Agency Coordination (GeoMAC).

    https://www.geomac.gov/. Accessed 18 Apr 2018.

U.S. Geological Survey (USGS) (2018b) National Elevation Dataset.

    https://earthexplorer.usgs.gov/. Accessed 18 Apr 2018.

Vadrevu KP, Eaturu A, Badarinath KVS (2010) Fire risk evaluation using multicriteria

    analysis—a case study. Environ Monit Assess 166:223–239.

    https://doi.org/10.1007/s10661-009-0997-3

Wigtil G, Hammer RB, Kline JD, Mockrin MH, Stewart SI, Roper D, Radeloff VC (2016) Places where wildfire potential and social vulnerability coincide in the coterminous United States. Int J Wildl Fire 25:896–908. https://doi.org/10.1071/WF15109

Yalcin A, Reis S, Aydinoglu AC, Yomralioglu (2011) A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey Catena 85:274-287. https://doi.org/10.1016/j.catena.2011.01.014

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 vulnerability components retained from the principal components analysis.

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

Table 3. The physical vulnerability 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 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.

Variable	Kendall Correlation	Binomial Regressions							
		Model #1 (AIC = 145.62)				**Model #2** (AIC = 136.74)			
Variable	tau	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	-0.33***	-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

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	---	---	---

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	2,297	574	1	0.3	0.3	3	2,297	766
Moderate Social - Moderate Physical	47 (15%)	4	6,580	1,645	0	0	0	4	6,580	1,645
High Social - Moderate Physical	26 (8%)	3	2,685	895	0	0	0	3	2,685	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	1,332	59	29,891	507
High Social - High Physical	21 (7%)	25	20,752	830	15	12,667	845	10	8,085	809

Table 8. 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 - 1,287.3	1,287.3 - 1,658.9	1,658.9 - 2,030.5
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 - 1,248.0	1,248.0 - 1,571.0	1,571.0 - 1,893.9	1,893.9 - 2,216.9	2,216.9 - 2,539.9
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 9. 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 10. The physical variable weightings produced by the analytical hierarchy process.

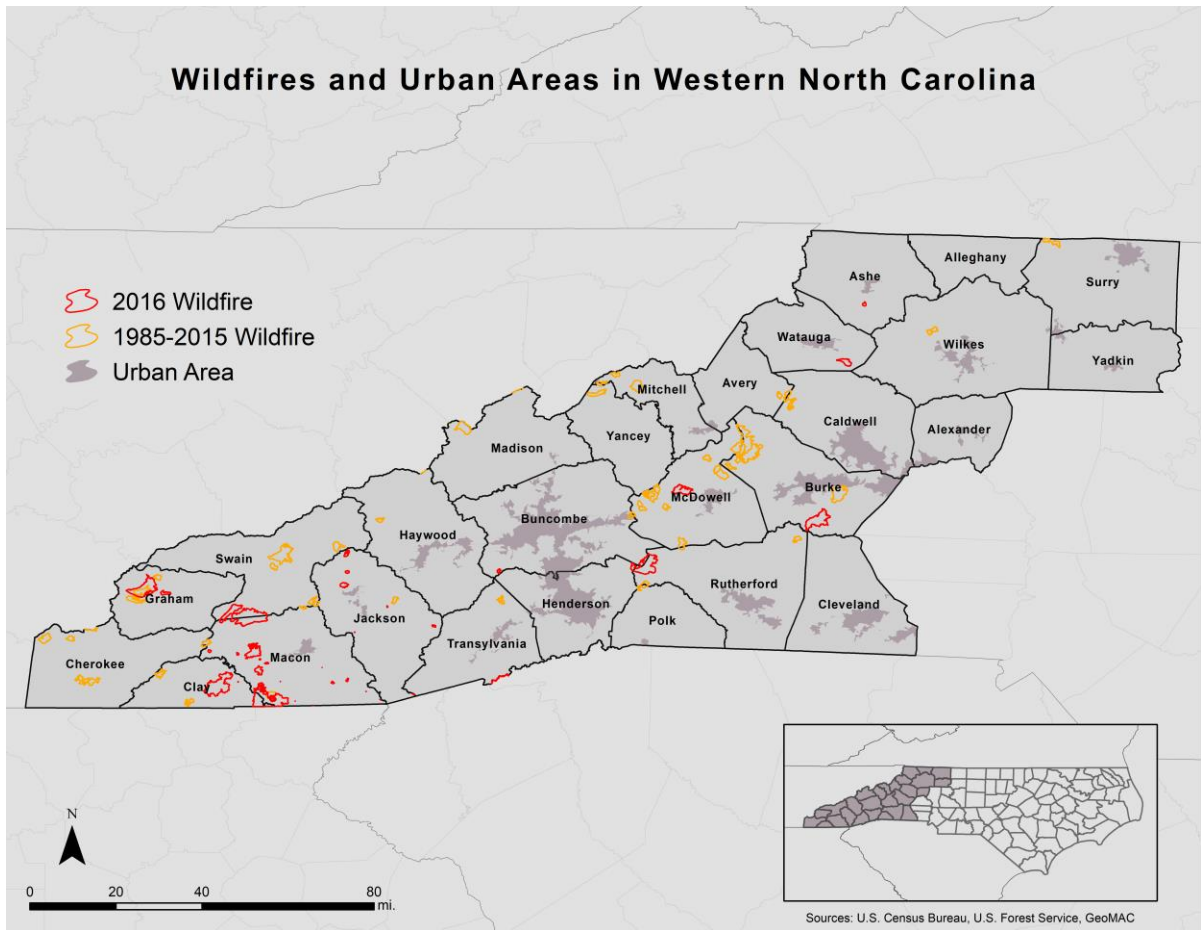| Variable	Weight
Aspect	7.2
Biomass	4.0
Elevation	15.8
Forest	16.1
Hillshade	10.2
Population	6.4
Precipitation	5.9
Road	16.4
Slope	11.1
Temperature	6.9

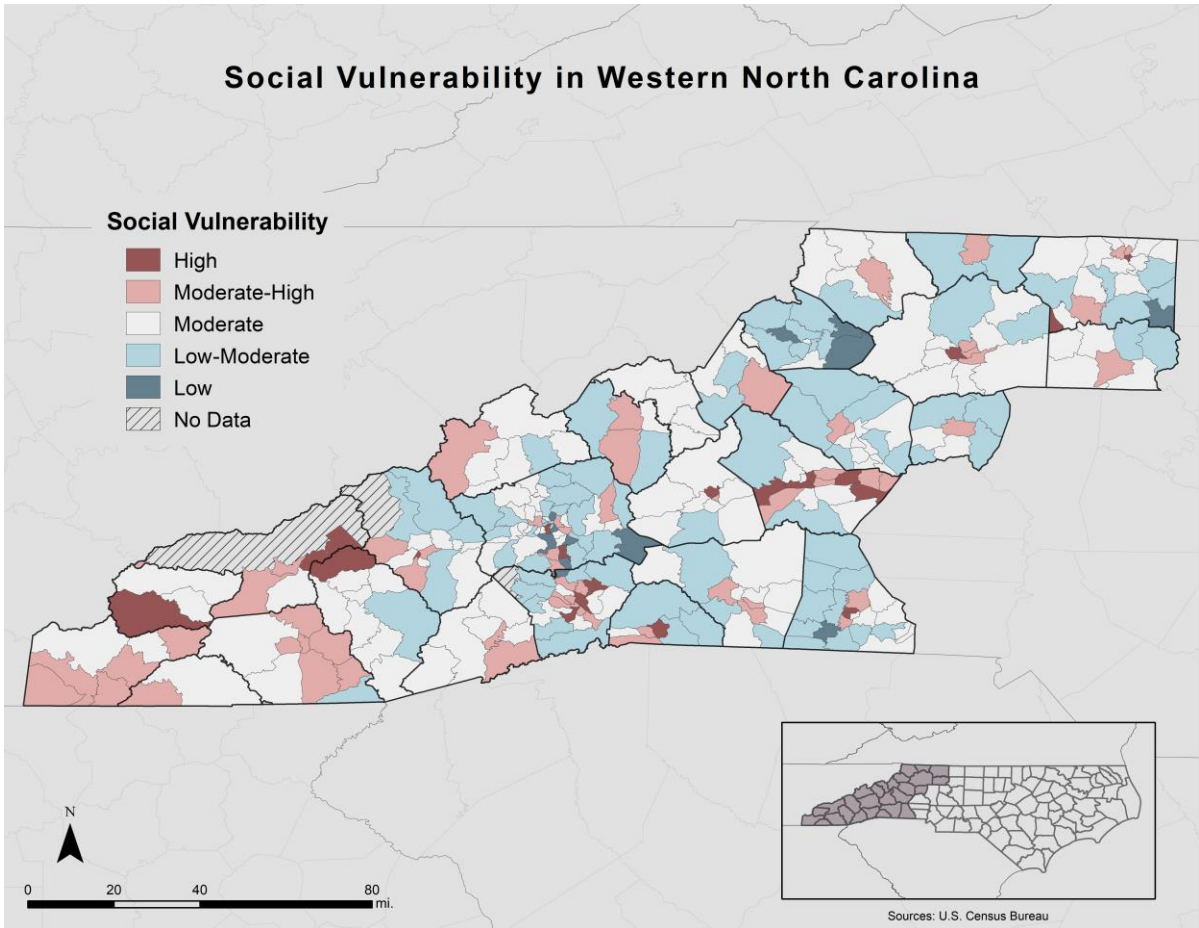**Fig. 1.** Wildfire perimeters and census-defined urban areas (50,000 or more people) in western North Carolina, USA.

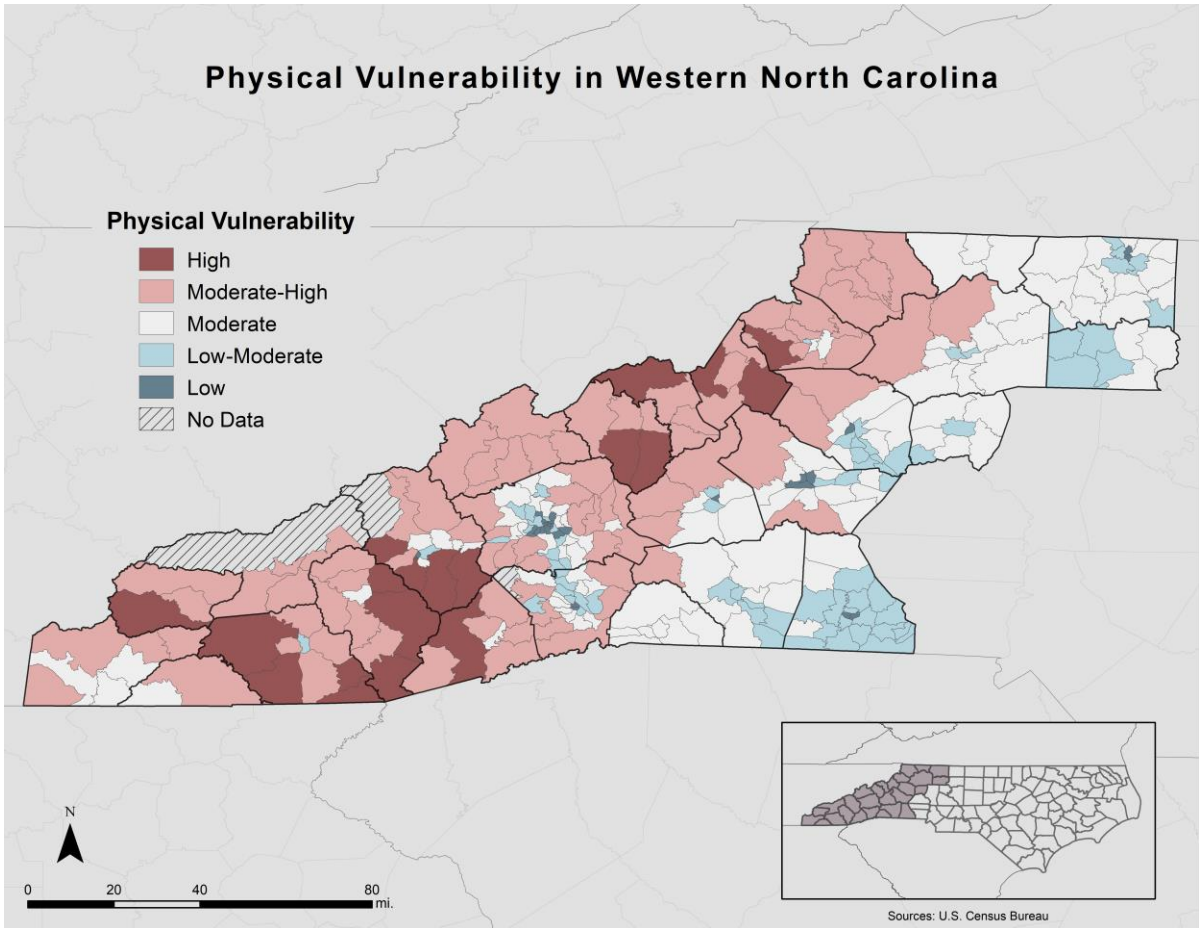**Fig. 2.** Social vulnerability scores for western North Carolina, USA.

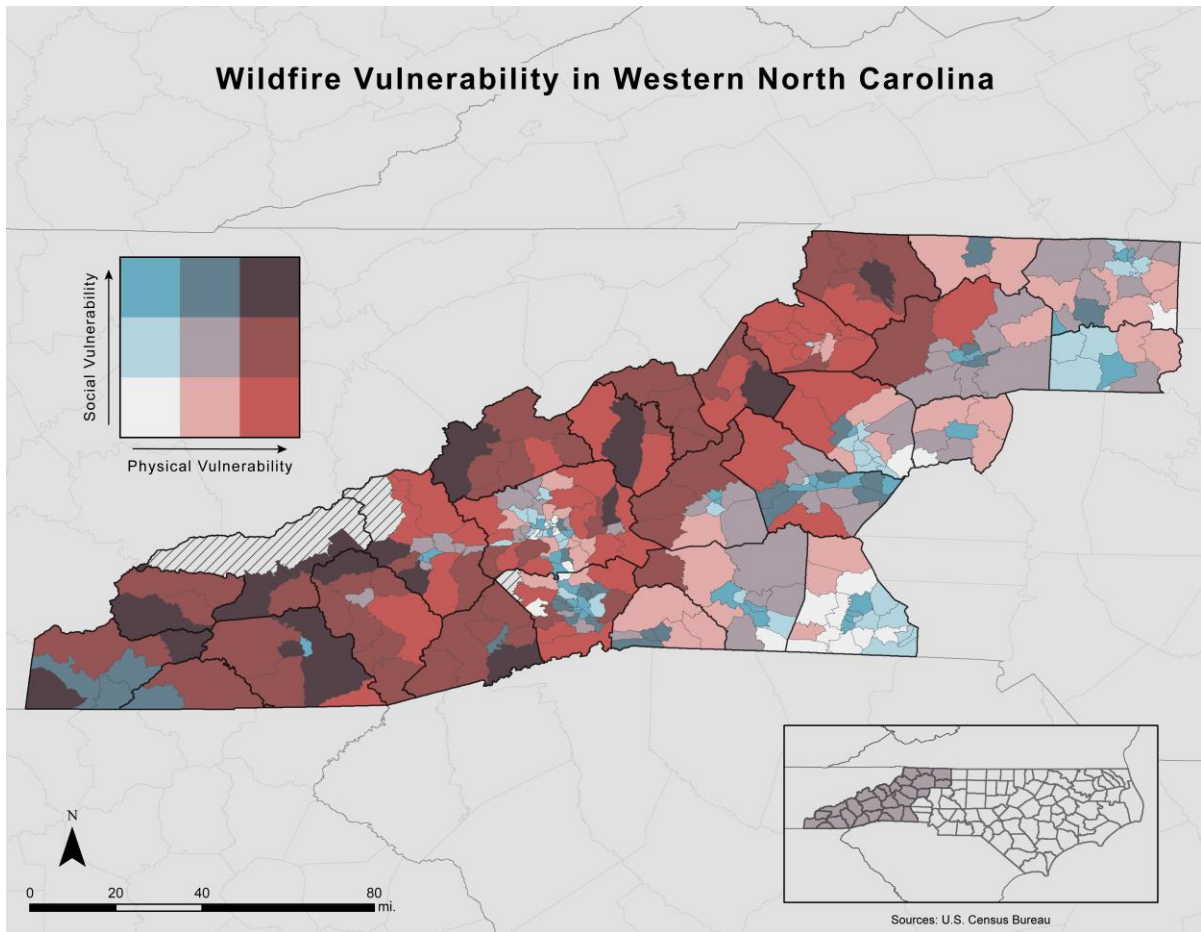**Fig. 3.** Physical vulnerability scores for western North Carolina, USA.

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

Vita

Lauren Margaret Andersen was born and raised in Charlotte, North Carolina. Her parents, Brett and Gay Andersen, instilled an appreciation for the mountains in her from a young age during camping trips to Wilson's Creek and Linville Gorge. After graduating from Covenant Day School in Matthews, North Carolina in May 2013, Lauren decided to follow in her parents' footsteps and attend Appalachian State University in Boone, North Carolina.

As an undergraduate, Lauren was a W.H. Plemmons Scholar and served on the executive board of Peel Literature & Arts Review, Geographical Society, Student Planning Association, and Appalachian State Chapter of the American Society for Photogrammetry and Remote Sensing. As a sophomore, Lauren was given the opportunity to conduct research on the spectral characteristics of local vegetation under the NASA North Carolina Space Grant and present at the State of North Carolina Undergraduate Research and Creativity Symposium and North Carolina Geographic Information Systems (GIS) Conference, which kick started her interest in research. Lauren's undergraduate thesis explored the impacts of the 2016 wildfire outbreak on Southern Appalachia. She graduated Summa Cum Laude with a Bachelor of Science in GIS and Community & Regional Planning in May 2017.

As a member of the Accelerated Admission Program, Lauren continued her research on wildfire vulnerability under the direction of Dr. Maggie Sugg. She began her second year of graduate school at Appalachian in August 2017. Throughout the year, Lauren had the opportunity to expand her work and present her research at the North Carolina American

Planning Association Conference and Department of Geography & Planning Speaker Series. She looks forward to presenting the culmination of her research and celebrating with her friends at the Association of American Geographers (AAG) Annual Meeting in New Orleans, Louisiana.

Upon graduating with a Master of Arts in Geography in May 2018, Lauren plans to enjoy one last summer in Boone before pursuing a career in GIS.