Assessing Climate Risk and Resiliency in Rural Appalachia

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EXECUTIVE SUMMARY

Rural communities are increasingly vulnerable to climate change because of their dependence on natural resources, physical isolation, limited economic diversity, and higher poverty rates.[1] With fundamental infrastructure already stressed in these systems, identifying vulnerable populations and anticipating climate impacts is essential to ensure that the significant adaptations needed for resiliency are available to these populations. In this project, researchers at Appalachian State University explored "climate vulnerability" and climate resilience "capacity" in rural western North Carolina (WNC), identifying areas with greater hazard exposure and socioeconomic vulnerability. This type of analysis is useful for local hazard mitigation planning and informing communications infrastructure planning for underserved rural areas. While the discussion on climate vulnerability and resilience as it relates to hazard exposure like flooding is often more focused on coastal regions, we wanted to evaluate the state of vulnerability and capacity for resilience in rural inland areas in the Southeast, using the Appalachian Region of western North Carolina as the focus. In this study we used regional data from Argonne National Laboratory (ANL) to identify areas of high risk to climate change, and connect socioeconomic disparities using geospatial analysis, for the purpose of achieving two primary outcomes:

1. Incorporate climate change data to produce comprehensive estimates of climate risk for hazard mitigation planning in rural western North Carolina
2. Identify socioeconomic disparities and associated climate vulnerability and resilience capacity in rural regions to inform policy and decision-making for underserved rural areas.

Through selected data analytics techniques, these two objectives were explored to produce some key findings relevant to understanding issues associated with building climate resilience capacity.

Objective 1

Planning for flooding resilience requires detailed information on where and when floods are expected to occur. A shortcoming of many hazard mitigation plans is that flooding exposure is aggregated to governmental boundaries, whereas decision-making concerning flood mitigation needs to consider which water bodies are most prone to flooding in order to make strategic investments. We generated baseline estimates of flooding exposure across the state of North Carolina using inland flooding heights from Argonne National Laboratory (ANL), monthly trends in precipitation quantity and variability, impervious surface data, and reported flooding events. Our findings suggest that high inland simulated flooding heights do not necessarily correlate with greater frequency of flooding events, but this could be a result of several reasons: 1) reported flood events are not necessarily in the same places with high inland flooding heights, 2) subjectivity in the community-level reporting systems for flood events could reduce the reliability of flood events reported, both in terms of quantity and characterization, and 3)

[1] Reidmiller, et al., (2018*). Impacts, Risk, and Adaptation in the United States. Fourth National Climate Assessment*, Volume 2, U.S. Global Change Research Program.

high inland flooding heights might occur in low risk areas, e.g. rural areas with less potential for property damages. Identifying the expected frequency of flooding at the watershed level is useful for evaluating the degree of exposure, prioritizing high risk areas, and guiding planning and decision-making for community resilience.

Objective 2

In our initial analysis regarding differential socioeconomic vulnerability across WNC, we find that the differences between WNC, particularly rural WNC, and the rest of the state are highly dependent on the way we assess vulnerability and resilience, but some common themes do exist. Regarding resilience, rural WNC has less governance and institutional (and infrastructure) capacity than the rest of the state. This means that rural WNC has, in general, less coverage for natural disasters, fewer mitigation policies in place, and less capacity in municipal expenditures for fire, police, and emergency management services. Some of this has to do with the exposure to natural hazards; rural WNC has less frequent exposure due to location, climate, and topography, but also limited experience with natural hazards when they do occur. We also have unique natural hazards, like landslides. At the same time, rural WNC demonstrates higher resilience scores in the social domain in one resilience indicator, despite lower scores from another indicator in the economic domain.

While WNC and its rural portions can be distinguished from the rest of the state using these national-level indicators of resilience, we wanted to investigate the concepts of resilience and vulnerability at a finer scale. We selected five counties in WNC that spanned the spectrum of the urban rural continuum codes; the five counties selected are Buncombe, Caldwell, Graham, Macon, and Watauga. We evaluated their exposure to certain hazards, specifically floods, wildfires, and landslides, the associated risks or amount of land impacted, and compared their social vulnerability and climate resilience based on relevan indicators and other sources of data. The results of this comparative analysis demonstrate that, while counties may be similar in some respects, e.g., topography, culture, governance, differences in socioeconomic characteristics can influence considerations for regional hazard mitigation planning. Particular attention may be needed for underserved populations that lack awareness of the need for climate resilience capacity and/or the economic means to build it.

Implications of our Findings

Providing more forward-looking information as well as education about potential costs of unmitigated climate vulnerability is needed to help integrate steps for building climate resilience capacity into hazard mitigation plans (HMPs). This also requires, however, an understanding of how socioeconomic variability among the county participants in regional HMPs can influence steps that are taken at the community level. Aided by the use of climate data like that from ANL, social vulnerability metrics, and climate resilience indicators that have been evaluated in this study, communities can better estimate impending hazard events and identify specific weaknesses in climate resilience at the local level, so that HMPs can be more effective in planning for the allocation of resources for specific community needs. Building resilience in populations that experience multiple vulnerabilities, as well as historical disenfranchisement, will require a clear understanding of how individuals' social networks affect their perceived ability to adapt to changing environmental conditions. In addition, this type of analysis can help identify weaknesses in resources needed at the community level, like communications infrastructure, so that planners can improve resilience capacity among those most vulnerable or underserved.

SECTION 1: PROJECT OVERVIEW AND OBJECTIVES

While over 95% of U.S. land is considered rural, only about 19% of the population lives there[2]. Rural natural resources, however, are the economic lifeblood to these communities, providing vital resources, e.g., food, energy, fresh water, to urban populations.[3] Rural communities are increasingly vulnerable to climate change because of their dependence on natural resources, physical isolation, limited economic diversity, and higher poverty rates.[4] Loss of young workers and dominant industries in the rural Southeast has exacerbated economic development and the means to make sweeping changes to combat direct and indirect impacts of climate change. With fundamental infrastructure already stressed in these systems, identifying vulnerable populations and anticipating climate impacts is essential to ensure that the significant adaptations needed for resiliency are available to these populations. In this project, researchers at Appalachian State University explored "climate vulnerability" and climate resilience "capacity" in rural western North Carolina (WNC), identifying hazard exposure vulnerability and associated socioeconomic disparities. This type of analysis is useful for local hazard mitigation planning and informing communications infrastructure planning for underserved rural areas.

The importance of rural America's natural resources to the country's economic and social well-being cannot be understated. Climate change risks in rural areas lack sufficient evaluation, however, which exacerbates the ability to plan appropriate responses to infrastructure needs, and to protect these valuable resources from potential hazards. While the discussion on climate vulnerability and resilience as it relates to climate change is often more focused on coastal regions, we wanted to evaluate the state of vulnerability and capacity for resilience in rural inland areas in the Southeast, using the Appalachian Region of western North Carolina as the focus. In collaboration with local officials in Watauga County, North Carolina, researchers at Appalachian State University used regional data from Argonne National Laboratory (ANL) to identify areas of high risk to climate change, and connect socioeconomic disparities using geospatial analysis, for the purpose of achieving two primary outcomes:

1. Incorporate climate change data to produce comprehensive estimates of climate risk for hazard mitigation planning in rural western North Carolina
2. Identify socioeconomic disparities and associated climate vulnerability and resilience capacity in rural regions to inform policy and decision-making for underserved rural areas.

The *research approach* for this project included the following:

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[2] U.S. Census Bureau, 2016: *American Community Survey*
[3] Kusmin L., 2009: "Rural America at a Glance, 2009 edition." *United States Department of Agriculture, Economic Research Service.* EIB-59.
[4] Hales, D., et al. 2014: "Ch. 14: Rural Communities. Climate Change Impacts in the United States: The Third National Climate Assessment." *U.S. Global Change Research Program*, 333-349

- Leveraging Argonne's available data as well as other sources of climate data to produce more informed estimates of exposure to natural hazards such as flooding, and evaluation of how climate change might reorganize the spatial patterns of precipitation. This produced comprehensive estimates of both baseline exposure to flooding and potential changes in seasonal precipitation patterns that can inform mitigation strategies, identify specific regional data needs, and guide decision-making on disparities between risks in inland rural areas versus urban or coastal impacts.

- Using relevant socioeconomic data for rural communities in western North Carolina to explore connections among rural disparities, climate vulnerability, and capacity for building resilience. Geospatial and statistical analysis were used to identify patterns of the spatial distribution of resilience and vulnerability. We are especially concerned in how rural WNC is unique in its resilience capacity and vulnerability. This analysis provides input to prioritize disadvantaged rural areas to improve climate resilience through informing hazard mitigation plans, infrastructure decisions, and economic development strategies in rural regions.

Significance or Impact of Project to Local Communities

Climate change impacts should not be addressed in isolation as a reaction to hazards but rather interwoven with the goal of decreasing socioeconomic disparities in rural areas.[5] Designing strategies for climate resilience that synergize with economic development and natural resource management maximizes strategic mitigation planning and resilience building. . We employed a case study of selected counties in Western North Carolina to highlight how socioeconomic disparities are connected to climate resilience capacity, and provide a discussion of implications.

The ultimate goal of this project is to inform planning for both policy makers (at local and state level) as well as how demonstrate how the use of various data analytics techniques can generate information that can assist with decision-making, particularly as it relates to resource needs for building climate resilience in communities (e.g., communications infrastructure decisions). In addition, the outcomes of this project will help guide our research to improve resilience capacity in rural regions, as well as further exploration on expanding the use of natural resources to build resilience.

Implications of COVID-19 Pandemic

During the course of this project, we experienced the effects of the COVID-19 pandemic, including significant changes to lifestyle that are connected to climate vulnerability and community resilience. In rural communities, small businesses were forced to close or operate at limited capacity, students shifted to remote learning, telehealth systems expanded, and employees began telecommuting. These changes in lifestyles highlighted the deficiencies in resilience in rural communities, particularly with respect to health care and communications infrastructure, but also economic well-being. It is clear that

[5] Wang, C., Guan, D., & Cai, W. *2019:* "Grand Challenges Cannot Be Treated in Isolation." *One Earth, 1. 24-26*

deficiencies in climate resilience must be evaluated in light of concurrent risks associated with other ongoing events that impact community lifestyles as well as capacity for mitigating deficiencies. The implications of the pandemic as they affect our project are discussed throughout this report as appropriate.

SECTION 2: LITERATURE REVIEW

2.1 Background

Recent years have seen a shift in the framing of disaster risk assessment and emergency management as discussed by researchers and practitioners in geography, community planning, public health, social services, economic development, and more. Specifically, the language of sustainability (e.g., sustainable development, sustainable communities, sustainability sciences) has given way to a discussion of resilience. This process has shifted the terms of the discourse, requiring a different set of data inputs, and generating research questions, findings, and potential actions with a somewhat new focus. This applies fully to the realm of understanding and communicating climate change impacts and disaster risk. For rural WNC, nestled in the Southern Appalachians, the primary climate risks and their likely impacts on residents require regionally specific data inputs and analytical methods that differ from those used in coastal and piedmont regions. These may yield locally meaningful vulnerability assessments and locally relevant measures with the potential to build community resilience; inform policies and programs that support residents; and address socioeconomic disparities.

2.2 Urban vs. Rural Resilience

As the concept of resilience gains dominance across disciplines relating to climate change and communities, debate continues about definitions and metrics, even as a general consensus forms that cities need to prepare for future climate stresses and shocks by building resilience. This effort should coincide with pursuit of global sustainable development goals.[6] To that end, planning should seek to address social inequities while promoting resilience, making use of the creativity and innovation that urban systems offer in pursuit of sustainable and resilient cities.

While urban resilience commands much of the attention, rural communities have been underrepresented in the climate resilience discussion. Rural communities, home to less than one-fifth of the US population yet occupying four-fifths of the land area, differ from urban communities in socio-demographics, literacy, occupation, income—and climate vulnerability. Lal et al. (2011) reviewed data from diverse sources (peer-reviewed journal articles, government reports and websites, and more) to identify possible climate change impacts on rural communities.[7] These include expanded growing seasons in the Northeast, and intense drought and rising energy costs in agricultural regions of the Southwest and Southeast. While

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[6] Leichenko, Robin. "Climate change and urban resilience." Current opinion in environmental sustainability 3.3 (2011): 164-168.

[7] Lal, R., Delgado, J. A., Groffman, P. M., Millar, N., Dell, C., & Rotz, A. (2011). Management to mitigate and adapt to climate change. Journal of Soil and Water Conservation, 66(4), 276-285.

rural communities face specific vulnerabilities, they also may have unique capacity for coping with and mitigating impacts.

Rural community resilience requires a balance among economic, social, and environmental needs (the 3Es of sustainability) in the face of challenges—internal and external: "Resilience is about communities being able to successfully weather the vicissitudes of endogenous and exogenous changes."[8] Three characteristics of rural communities (economic capital, social capital, environmental capital) provide a framework for discussing rural resilience that extends beyond their agricultural or resource-based past. Moreover, Molnar (2010) noted that the focus on rural environments, household welfare, community, and livelihoods is now being heightened by climate change; its differential impacts across rural communities; and how they cope with existing and emerging challenges.[9]

Similarly, the importance of rural commerce in community resilience cannot be understated; through direct pathways (jobs, goods, and services) and indirect benefits of economic development (e.g., stable population), community resilience relies on the business community. Rural business owners have the local knowledge and motivation to respond to local conditions "and to proactively and skillfully turn them into entrepreneurial opportunities," in the process becoming active players in adaptation and change agents in promoting rural community resilience[10] .

2.3 North Carolina and Appalachia

The southern United States is particularly socially vulnerable to climate hazards. Adapting the Social Vulnerability Index (including variables for infrastructure and built environment) to include social and demographic variables more reflective of social well-being, Emrich & Cutter (2011) identified elevated drought hazard exposure concentrated in Appalachia, specifically western North Carolina, as well as moderate and elevated multi-hazard risk in the area.[11]

In light of increasing exposure to extreme weather events over the past half-century, particularly in the US Southeast and Southwest, Preston (2013) used demographic data to create scenarios of future county-level population changes and historical changes in wealth,

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[8] Wilson, G., 2010. "Multifunctional 'quality' and rural community resilience." *Transactions of the Institute of British Geographers, 35* (3)
[9] Molnar, J. J., 2010. "Climate change and societal response: Livelihoods, communities, and the environment." *Rural Sociology, 75* (1), 1-16
[10] Steiner, A., and J. Atterton, 2015. "Exploring the contribution of rural enterprises to local resilience." *Journal of Rural Studies, 40,* 30-45
[11] Emrich, Christopher T., and Susan L. Cutter, 2011. "Social vulnerability to climate-sensitive hazards in the southern United States." *Weather, Climate and Society, 3* (3), 193-208

and to estimate future losses from extreme climate events. Results suggest economic losses growing by a factor of 1.3-1.7 by 2025, and by 1.8-3.9 by 2050.[12] Further, an exploratory study employed spatial data for population growth, natural land loss, and climate change data to identify 'hotspots' of projected climate change in the U.S. Although such concentrations occurred across the nation, 'hotspots' of projected natural land loss clustered in the Southeast, particularly in the Piedmont region of North and South Carolina, with a distinctive band in the Appalachian region.[13]

2.4 Equity dimensions of climate risk and resilience

Rural climate vulnerability has social equity dimensions. Some argue that in the debate over the most effective and meaningful approaches to hazard risk assessment, social vulnerability has been severely underrepresented. In one study analyzing the records for 1500 Hurricane Ike-damaged single-family homes, researchers found that hazard exposure, structural characteristics, and socioeconomic characteristics were significant predictors of structural damage; this suggests that such assessments may be useful tools for promoting resilient communities.[14]

Building community resilience to climate change in rural, farming-dependent areas requires decision-makers to "embrace a "social justice" perspective and an understanding of science as transformative of society." Furman et al. (2014) analyzed quantitative and qualitative data from a sample of 98 African-American farmers in the Southeastern U.S. Facing the same risks and stresses as other small farmers (e.g., rising land costs, policies that favor mass-scale farming), African-American farmers are "vulnerable to drought and other climate anomalies due to their limited resource base, residence in remote countries, and advanced age," while also struggling with injustices rooted in racism. [15]

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[12] Preston, Benjamin, 2013. "Local path dependence of U.S. socioeconomic exposure to climate extremes and the vulnerability commitment." *Global Environmental Change, 23* (4), 719-732

[13] Neelam C. Poudyal, Duncan Elkins, Nathan Nibbelink, H. Ken Cordell, Buddhi Gyawali (2015). An exploratory spatial analysis of projected hotspots of population growth, natural land loss, and climate change in the conterminous United States. Land Use Policy, Volume 51, P 325-334

[14] Highfield, Wesley E., Walter Gillis Peacock, and Shannon Van Zandt, 2014. "Mitigation planning: Why hazard exposure, structural vulnerability, and social vulnerability matter." *Journal of Planning Education and Research, 34* (3), 287-300

[15] Furman, C., C. Roncoli, W. Bartels, M. Boudreau, H. Crockett, H. Gray, and G. Hoogenboom, 2014. "Social justice in climate services: Engaging African American farmers in the American South." *Climate Risk Management, 2,* 11-25

2.5 Planning and policy for climate resilience

Despite significant climate change impacts felt across the U.S. and world, making adaptation measures urgent, climate resilience research is still in its infancy (Wilbanks & Kates, 2010, Lyles et al., 2016). In addition, the integration of climate resilience measures into local hazard mitigation plans is not widely practiced. For example, Stults (2017) analyzed 30 local hazard mitigation plans for integration of climate change with FEMA's Plan Review Crosswalk checklist, and found that most (23 of 35 plans) explicitly discussed climate change impacts on natural hazards. Even so, while many communities anticipate a changing climate, few have formally committed to adaptation measures.[16] Communities may benefit from guidance on integrated hazard mitigation planning and engaging "nontraditional stakeholders such as experts in climate science, local organizations working on climate mitigation and adaptation, regional organizations, and the most vulnerable residents." Better outcomes may be achieved with early and repeated stakeholder input [17]. Practitioner and stakeholder responses provide guidance on shaping future climate resilience and sustainability policy application, specifically when it comes to the process of collecting community input and challenges related to "stakeholder concerns, practitioner preferences, and uncertainty under future (climate change) conditions."

Finally, a survey of state Hazard Mitigation Officers in the 56 U.S. states, territories, and the District of Columbia that participate in FEMA's Hazard Mitigation Grant Program revealed the extent to which Hazard Mitigation Plans (HMPs) have incorporated climate change. Although most of the respondents reported that HMPs address climate change, motivated by growing evidence and projections of climate change, they also reported barriers to integrating climate change, such as lack of funding and competing priorities; political priorities were cited both as facilitating and hindering integration.[18] Better evidence-based hazard mitigation policy and practice will require effective translation of climate change research for practitioners.

2.6 Information and communication technology and the rural digital gap

There is no question that access to an effective communications infrastructure is essential to building climate resilience in rural communities. Yet, access in rural areas is exacerbated by

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[16] Stults, Missy, 2017. "Integrating climate change into hazard mitigation planning: Opportunities and examples in practice." *Climate Risk Management, 17,* 21-34

[17] Goldsmith, Windi, and Thomas Flanagan, 2017. "Value methodology—Case studies within climate resilience and sustainability policy application." *Architectural Engineering & Design Management, 13* (1), 3-21

[18] Gonick, Shannon A., and Nicole A. Errett, 2018. "Integrating climate change into hazard mitigation planning: A survey of state hazard mitigation officers." *Sustainability, 10* (11)

both physical and socioeconomic barriers due to insufficient prevalence of broadband technology or inability to afford it. The scant literature on rural information and communication technology (ICT) is heavily focused on the technical dimensions of the urban/rural digital gap, overshadowing a discussion of ways rural communities have selectively incorporated some digital technologies into social and economic systems.

Ashmore et al. (2015) describe the importance for rural residents of Internet technology and access, and discusses how high-speed broadband, and its impact in everyday routines and in personal skill-building and empowerment, may promote resilient rural communities. They note the often "contradictory nature of the relationship between superfast broadband, rural users and potential individual and community resilience."[19]

[19] Ashmore, F. H., J. H. Farrington, and S. Skerratt, 2015. "Superfast broadband and rural community resilience: Examining the rural need for speed." *Scottish Geographical Journal, 131* (3-4), 265-278.

SECTION 3: HAZARD EXPOSURE FROM CLIMATE CHANGE IMPACTS (Objective 1)

3.1 Background for this section

Heavy precipitation events impact communities due to inland flooding, destabilization of the ground resulting in landslides, and other hazards that can cause property damage, loss of life, and injury. Significant damages from heavy precipitation and other storms have been increasing in the past decade [20], and models project that the frequency and intensity of flooding is expected to increase in many areas of the United States[21].[22] Decision-makers need information concerning potential current and future risks of heavy precipitation to stimulate mitigation planning and strategic development. This has ultimately been shown to substantially reduce financial burden from disaster[23] [24] [25].

Characterizing risk and exposure is an essential component for building community resilience; a community cannot respond, adapt, and rebound from natural hazards if they do not have some expectation of intensity of exposure and overall risk to a system. The Federal Emergency Management Agency (FEMA) provides tools to help identify potential losses and provides funding for community mitigation efforts.[26] In addition to FEMA, a few resilience indicators have been suggested to assess a communities' baseline ability to absorb and adapt to hazardous events. [27] [28] [29] Although each of these tools are informative, they either treat climate as static or provide only a baseline of resilience. This approach can be problematic because, used alone, historic probabilities of hazards events cannot effectively characterize future hazards under a changing climate. Incorporating available climate projection data can assist in estimating future exposure and the need for more effective mitigation strategies in a community.

Watersheds are dynamic unique systems that respond to heavy precipitation individually in the headwaters, but collectively as water migrates downstream. This individual response is the coupling

[20] Smith, A. B. & Arndt, D. S. US Billion-dollar weather and climate disasters over the last 40 years (1980-2019)-in historical context. in *100th American Meteorological Society Annual Meeting* (AMS, 2020).
[21] Maurer, E. P., Kayser, G., Doyle, L. & Wood, A. W. Adjusting flood peak frequency changes to account for climate change impacts in the western United States. *J. Water Resour. Plan. Manag.* **144**, 5017025 (2018).
[22] Marsooli, R., Lin, N., Emanuel, K. & Feng, K. Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nat. Commun.* **10**, 1–9 (2019).
[23] Godschalk, D. R., Rose, A., Mittler, E., Porter, K. & West, C. T. Estimating the value of foresight: aggregate analysis of natural hazard mitigation benefits and costs. *J. Environ. Plan. Manag.* **52**, 739–756 (2009)
[24] Shreve, C. M. & Kelman, I. Does mitigation save? Reviewing cost-benefit analyses of disaster risk reduction. *Int. J. disaster risk Reduct.* **10**, 213–235 (2014)
[25] Laub, P. M. *Report on costs and benefits of natural hazard mitigation*. (DIANE Publishing, 1997).
[26] Zhou, H., Wan, J. & Jia, H. Resilience to natural hazards: a geographic perspective. *Nat. hazards* **53**, 21–41 (2010)
[27] Cutter, S. L., Burton, C. G. & Emrich, C. T. Disaster resilience indicators for benchmarking baseline conditions. *J. Homel. Secur. Emerg. Manag.* **7**, (2010).
[28] Cutter, S. L. The landscape of disaster resilience indicators in the USA. *Nat. hazards* **80**, 741–758 (2016).
[29] Summers, J. K., Harwell, L. C., Smith, L. M. & Buck, K. D. Measuring community resilience to natural hazards: the natural hazard resilience screening index (NaHRSI)—development and application to the United States. *GeoHealth* **2**, 372–394 (2018)

among its topography, soil characteristics, vegetation, underlying geology, and human impacts [30]. Most watershed modeling approaches simulate flooding events by incorporating some of these characteristics into a process-based model.[31] These are informative exercises, but are highly reliant on computation demand, careful structure of input parameters, and user expertise[32] [33] . Statistical, or data driven, modeling can provide additional inferential capacity, and can be used in conjunction with process modeling to provide comprehensive information concerning exposure[34].

Climate change is often talked about at the global scale, but local decision-makers need to be aware of potential climate changes within their own community[35]. Even national or state level reporting on the changes within the climate do not help local communities plan for the alterations of seasonal dynamics that could cause hazards such as flooding or drought, impacting economic livelihood and human health. For example, the recent North Carolina Climate Science report does provide some coarse insights into the regional trends in climate[36]. But, the diversity of environments within regions such as Western North Carolina (WNC) cause these predictions to lack some of the specificity for localized decision-making. Annual precipitation is expected to increase across the state of North Carolina as well as the number of days with extreme precipitation events. Knowing this accentuates the need for reliable estimates of localized exposure to flooding for appropriate natural hazard planning.

In the face of climate change, and with the availability of downscaled future climate data from WorldClim[37] [38], it could benefit hazard mitigation planning to incorporate this high-resolution data to assess both current and future climate risks and seasonal changes. Our initial goal was to use the Argonne national laboratory (ANL) climate data, available high-resolution climate data for current and potential future precipitation patterns, national level impervious surface data, and locations of flooding events to assess expected occurrence of flooding within the state of North Carolina. This baseline estimate of flooding exposure was then used in conjunction with monthly precipitation data and the ANL data to explore whether we can find consistent patterns among watersheds in the potential changes in precipitation. Although monthly patterns in precipitation cannot accurately simulate the sporadic nature of extreme weather that causes floods, it provides a better baseline (than historical data

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[30] Merz, B. *et al.* Floods and climate: emerging perspectives for flood risk assessment and management. *Nat. Hazards Earth Syst. Sci.* **14**, 1921–1942 (2014).
[31] Daniel, E. B. *et al.* Watershed Modeling and its Applications : A State-of-the-Art Review. 26–50 (2011).
[32] Shirmohammadi, A. Uncertainty in TMDL Models. *Trans. ASABE* **49**, 301–314 (2006).
[33] Leskens, J. G., Brugnach, M., Hoekstra, A. Y. & Schuurmans, W. Why are decisions in flood disaster management so poorly supported by information from flood models? *Environ. Model. Softw.* ***53**, 53–61 (2014).*
[34] Solomatine, D. P. & Price, R. K. Innovative approaches to flood forecasting using data driven and hybrid modelling. in *Hydroinformatics: (In 2 Volumes, with CD-ROM)* 1639–1646 (World Scientific, 2004).
[35] Howarth, C. & Painter, J. Exploring the science–policy interface on climate change: The role of the IPCC in informing local decision-making in the UK. *Palgrave Commun.* **2**, 16058 (2016).
[36] Kunkel, K. E. *et al. North Carolina State climate report*. (2020)
[37] Fick, S. E. & Hijmans, R. J. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *Int. J. Climatol.* **37**, 4302–4315 (2017).
[38] Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G. & Jarvis, A. Very high resolution interpolated climate surfaces for global land areas. *Int. J. Climatol.* **25**, 1965–1978 (2005).

alone) for local communities to assess high risk watersheds and localized changes to their precipitation patterns. This section summarizes the work in association with achieving objective 1: *Incorporating climate change data to produce comprehensive estimates of climate risk for hazard mitigation planning in rural western North Carolina.*

3.2 Evaluation of Argonne National Laboratory Data

AT&T collaborated with ANL to develop the AT&T's Climate Change Analysis Tool. The result of this collaboration is a dataset generated from climate model simulations using current (1995-2004) data and future (2045-2054) projections. The simulations generated return periods for 10-year and 50-year storms and produced the following sets of variables: inland flooding, associated wind speeds with a given storm, and coastal flooding. The 5th, 50th, and 95th percentiles are included for storm return periods of 10-years and 50-years, and the general extreme value distribution parameters are included to extract projections for any n-year return period.

We used inland flooding data across the state of North Carolina, but we focus our attention in this general discussion to a 27-county region described as WNC (Figure 3.1). The 27 counties we describe as WNC represent a range of different types of communities (See Table A.1 in Appendix). All but two of the Rural Urban Continuum codes from the United States Economic Research Service are represented[39]; most of the counties in WNC are non-metro areas, with eight counties classifying as completely rural communities.

Inland flooding was simulated by the WRF-Hydro® model (Version 5). This process model simulates the entire hydrological cycle for watersheds within a study area, using inputs such as climate variables, topography, and vegetation to inform a physics-based model. The outputs from this model include depth of surface water accumulation (the inland flooding data presented here), but also stream flow and flood duration. The data were packaged in a .csv file for public use, and this contains over 19,272,189 observations across the Southeastern United States. For faster processing capabilities, we first removed all zeros from this dataset, leaving 823,274 nonzero observations for analysis. This included 150,860 observations within the state of North Carolina and 12,513 when constrained to 27 counties in North Carolina identified as WNC.

[39] Parker, T. *Rural-urban continuum codes*. (2013).

Flooding events are spatially constrained by watershed boundaries. Although hazard planning occurs along political boundaries, e.g. city, county, or regional level, decisions concerning flooding occurrence need to consider watershed boundaries. Because of this, we used 12-digit hydrologic codes from the United States Geological Survey in developing a flooding exposure model. This included 1775 watersheds within North Carolina, and 441 watersheds in the WNC region. For each return period, we calculated the mean flood height in each watershed using the median and the 95th percentile estimates of flood heights at the specific points mentioned above.

The watersheds with the highest average surface flooding height for the median 10-year and 50-year event is Fires Creek in Clay County for WNC and for the state of North Carolina, Carrot Creek in Carteret County. The maximum flood height at a single point in a watershed for WNC was the Upper Linville River in Avery County for a 10-year event, and Grassy Creek of the Lower Little River in Alexander County for a 50-year event. Figure 3.1 shows the distribution of 10-year and 50-year mean flood heights for each watershed.

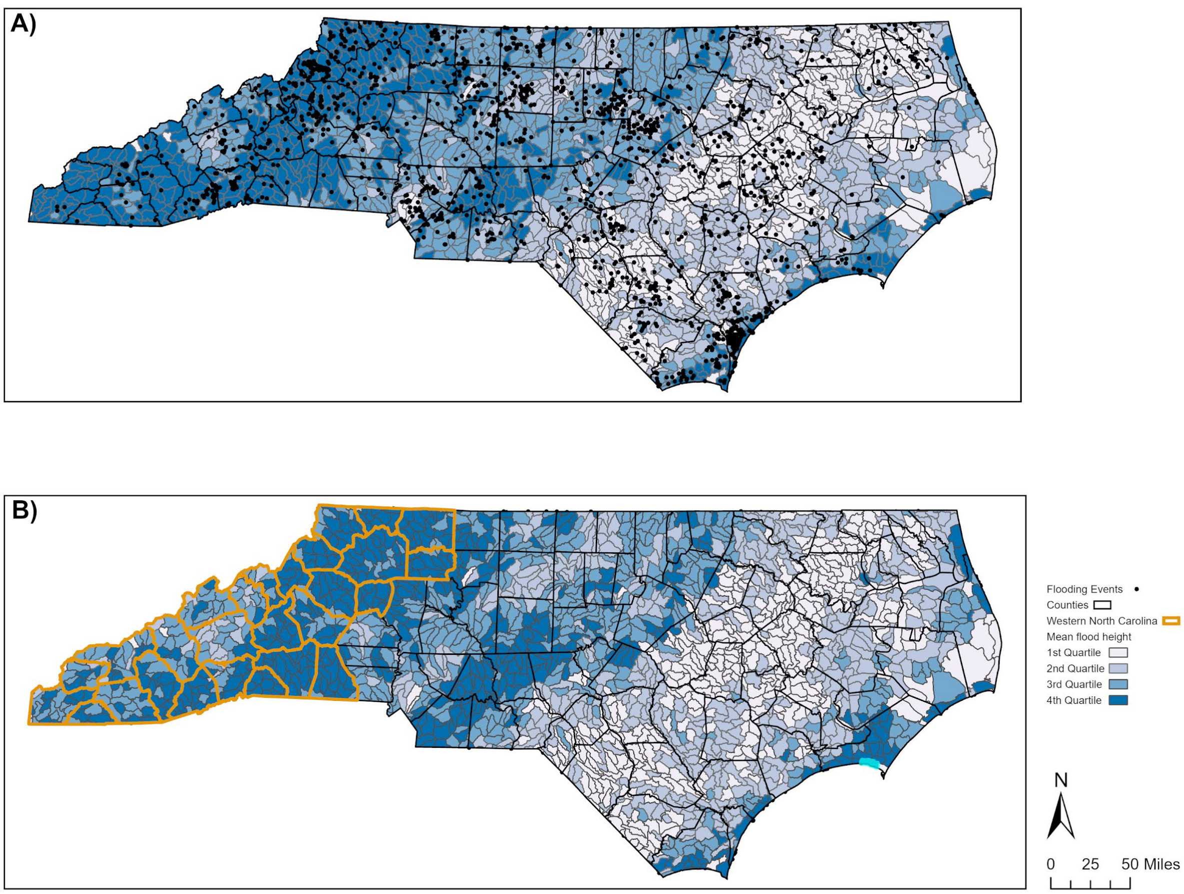

Figure 3.1. *North Carolina HUC-12 watershed boundaries, county boundaries, and the mean flood heights for (A) 10-year and (B) 50-year flood events. Flood heights are based on the median values of the distribution of inland flooding heights provided by Argonne. These were averaged within a watershed and divided into quartiles for easier visualization. Flooding events from 2010-2019 are shown as well as the 27 county region defined as Western North Carolina (WNC).*

3.3 Evaluation of National Flooding Events Database for North Carolina

The Flooding events data is available from the National Center for Environmental Information (NCEI) flooding events database[40]. We selected all events across the state of North Carolina of the type "Flood" and "Flash Flood" for the years 2010-2019. The beginning locations of each flooding event were joined to each watershed, allowing for a count of events over this decade. We also evaluate county by county flooding events in terms of frequency and associated damages to property, crops, and the population (deaths and injuries). These counts were used as the response variables for the Zero Inflated Poisson (ZIP) regression modeling analysis to assess flooding risk (sect 3.5).

There were 1,861 flooding events recorded during this time period, with property losses totaling over a billion dollars and crop losses of over $600 million (Table 3.2). These also resulted in four documented injuries and 48 deaths. The most flooding events occurred in 2018, while 2016 was the most expensive year in terms of property and human life losses. Three counties in WNC were represented in the top ten counties with flooding occurrences (Watauga, Transylvania, and Henderson). WNC county flooding events and costs are also shown in Table 3.1. Other notable counties include three most populated counties: Wake (Raleigh area), Guilford (Greensboro), and Mecklenburg (Charlotte); three coastal counties (New Hanover, Brunswick, and Pender); and one other county in a metropolitan area (Rockingham).

[40] NCEI. Storm Events Database. https://www.ncdc.noaa.gov/stormevents/ (2020).

Table 3.1.

Evaluation of frequency and expense of flooding events for the decade 2010 – 2019 for North Carolina.

Year	Number of flood events	Total property costs (Thousands $)	Total crop costs (Thousand $)	Deaths	Injuries
2010	269	6839	69610	8	0
2011	147	7644	5	2	1
2012	103	1266	0	0	0
2013	216	23627	30	0	0
2014	109	2854	5	0	2
2015	196	1793	0	0	1
2016	245	721307	171000	24	0
2017	104	1549	0	1	0
2018	359	229429	430030	12	0
2019	113	3710	0	1	0

The distribution of storms by months for each year is provided in Figure 3.2. Three months during this time period had over 100 flooding events: September of 2010 and 2018, and October of 2016. Other notable periods of storm events were the summer floods of 2013, where between June and July of that year 141 flooding events occurred. The period of time from September to October 2016 was the most costly period of flooding events, with 890 million dollars in damages to property and crops. This period of time was also the deadliest, with 24 lives lost.

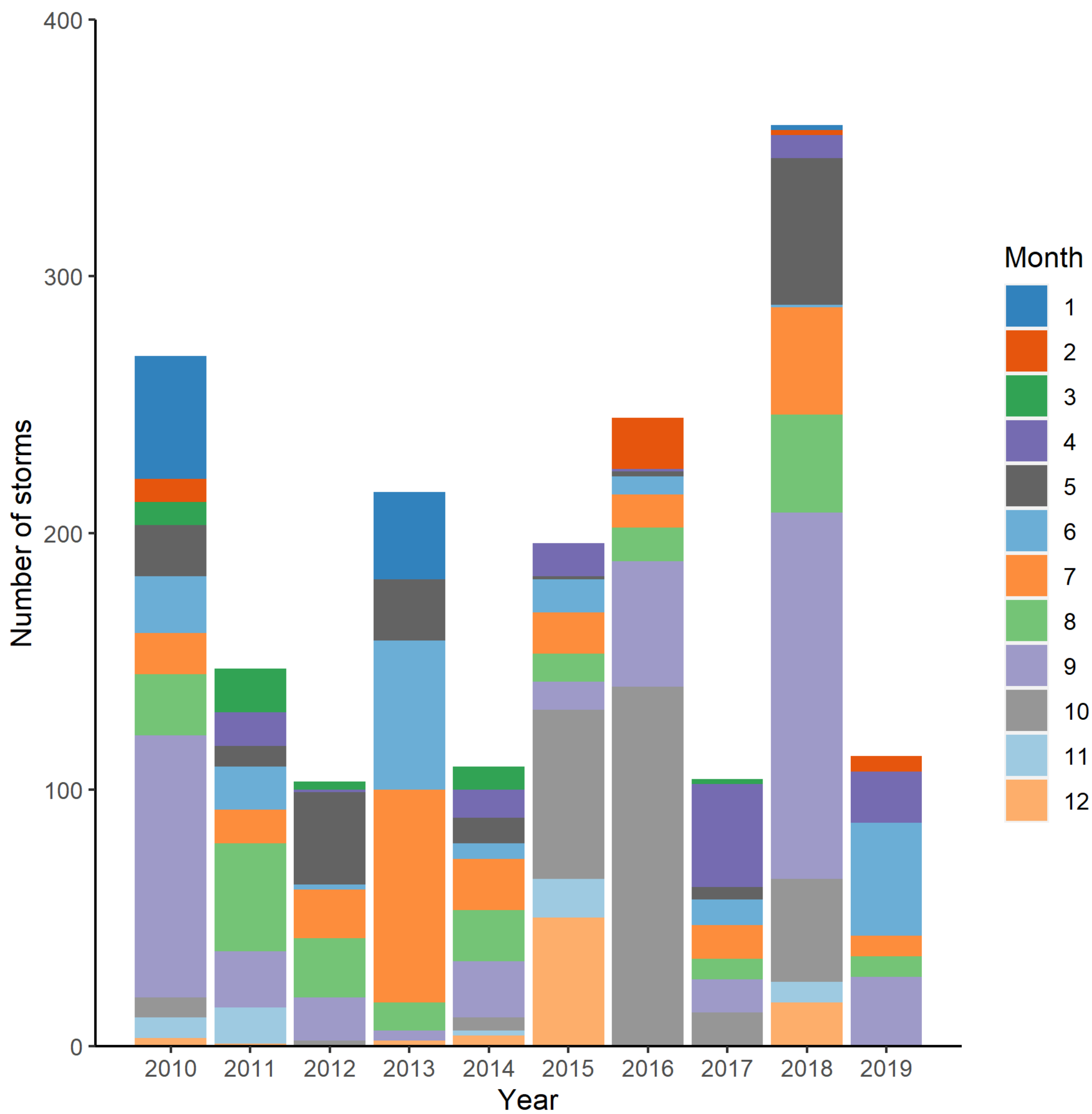

Figure 3.2. *Distribution of flooding events by year and by month for the time period of 2010-2019 for North Carolina*.

3.4 Precipitation and impervious surface data for North Carolina

Flooding is a product of topography, precipitation intensity and duration, soil type, vegetation, and stormwater management practices. The available Argonne data uses a landscape processing model which includes soil type, vegetation, and topography. Along with these projected flood heights from Argonne, we used potential precipitation data and one specific human impact, impervious surfaces, to assess expected flooding exposure.

For current precipitation trends, 30-year normals are available from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) research group at Oregon State University[41]. Data with resolution of 800 m^2 was selected for annual and monthly precipitation. High resolution downscaled data for climate change scenarios is available from WorldClim[42] [43]. Although WorldClim does have 30-year normal data, it only represents 1970-2000, rather than the more recent 1980-2010 data from PRISM. For our initial modeling purposes, we selected all monthly precipitation values from PRISM and calculated the coefficient of variation for monthly precipitation. These values were averaged across each watershed. Impervious surface data is provided by the Multi-Resolution Land Characteristics (MRLC) consortium at 30 m^2 resolution, and we determined the average impervious surface located within the watershed using the 2016 update[44].

3.5 Zero-inflated Poisson modeling approach

To assess potential flooding risk in watersheds across North Carolina, we used the ZIP regression modeling approach. The response variable is the number of storm events within a watershed that was extracted from the NCEI storm events database (Section 3.3) and the explanatory variables were the inland flooding heights from ANL (Section 3.2), monthly precipitation totals from PRISM (Section 3.4), and percent impervious surface from MRLC (Section 3.4).

Count data are most appropriately modeled by a Poisson regression; however, since many watersheds were shown to have zero flooding events during 2010-2019, we opted to use a ZIP model in this analysis. In a ZIP model, each observation is one of two cases: case 1 states that the count is zero, while case 2 states that the counts (including zeros) is generated using a Poisson model. Case 1 occurs with probability π and case 2 occurs with probability$1-\pi$. The probability distribution for event y_i is given as follows:

$$Pr\ Pr\ (y_i = j)\ = \{\pi_i + (1-\pi_i)\ exp\ exp\ (-\mu_i)\ \ (1-\pi_i)\frac{\mu_i{}^{y_i} exp(-\mu_i)}{y_i!} \quad if\ j = 0\ if\ j > 0$$

Where the Poisson component is

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[41] Daly, C., Taylor, G. H. & Gibson, W. P. The PRISM approach to mapping precipitation and temperature. in *Proc., 10th AMS Conf. on Applied Climatology* 20–23 (Citeseer, 1997).
[42] Ibid, N 37
[43] Ibid, N 38
[44] Homer, C., Dewitz, J., Jin, S. & Xian, G. Z. Completion of the 2016 National Land Cover Database, Revealing Patterns of Conterminous US Land Cover Change from 2001 to 2016. *AGUFM* **2019**, B24A-03 (2019)

$$\mu_i = exp(\beta_o + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots \beta_m x_{mi})$$

and the logistic link function π_i is:

$$\pi_i = \frac{\lambda_i}{1+\lambda_i}$$

$$\lambda_i = exp(\alpha_o + \alpha_1 z_{1i} + \alpha_2 z_{2i} + \cdots \alpha_m z_{mi})$$

One of the benefits of this approach is that the response for inflated zeros (the logistic component) can be modeled with different predictors than the Poisson component. The expected value, in our case the number of flood events in a 10-year period, is a product of the Poisson component, μ_i, and the probability that the event is not a zero, $1 - \pi_i$.

We used a bootstrapped aggregation approach to predict the expected number of flooding events, and to compare the accuracy of traditional Poisson regression (μ_i), and two ZIP models: a full model using all available data and a model which in each bootstrapped sample used backwards elimination as a variable subset selection method. Bagged models were compared using optimism-corrected root mean square error (RMSE)[45]. The number of bootstrapped samples for each of the bagged models was 1000. The bootstrapping ZIP approach was performed in R 4.0.2.

3.6 Results of Zero-Inflated Poisson Regression Analysis

Naïve (in-sample) RMSE estimates were 2.15, 1.05, and 1.03 for the Poisson, ZIP with backward elimination, and ZIP with all variables respectively. However, when corrected using optimism, the backwards elimination ZIP performed 10 % better than Poisson regression, and 33 % better than the ZIP using all variables. Since this model is a mixture of a Poisson model and a logistic model, we present two measures to assess the relative strength of association between the parameters and the count or zero component of our model (Table 1.3). For the count component we used the incidence rate ratio (IRR); this is interpreted as the rate ratio for a one standard deviation increase in the explanatory variable, given everything else is held constant. As an example, the IRR for a 50-year flood event is 2.11 (95% CI: 1.28, 4.61) (Table 1.3) This means the 50-year flood event that is one standard deviation above the mean would be expected to see counts increase by a factor of 2.11. The zero component of the model, we assessed this using the odds ratio. Using May precipitation as an example, the odds that the observation is zero increases by a factor of 2.74 (95% CI: 1.05, 15.06) for a one standard deviation increase in May precipitation, holding all other explanatory variables constant.

Our findings suggest that expected flooding height does not necessarily mean more flooding events. There was an conflicting component of flood heights for different return periods; the strongest effect was that increased 10-year flood height would lead to lower probability that a watershed had zero flooding events (OR 0.17, 95% CI: 0.02, 0.59), but the higher the 50-year flooding height, the more likely the watershed has a count of zero (OR: 6.52, 95% CI: 1.35, 72.68). Both 10-year and 50-year flood

[45] Tibshirani, R. J. & Efron, B. An introduction to the bootstrap. *Monogr. Stat. Appl. Probab.* **57**, 1–436 (1993)

heights demonstrate a similar pattern for the count component of the regression, where higher 50-year floods heights meant higher expected counts, but this was offset by lower expected counts for higher 10-year flood events; however, the effect was not as pronounced (Table 3.2). This suggests that higher simulated flooding heights do not necessarily correlate with greater frequency of floods. This could be a result of several reasons: 1) Reported flood events are not necessarily in the same places with high inland flooding heights, 2) Subjectivity in the community-level reporting systems for flood events could reduce the reliability of flood events reported, both in terms of quantity and characterization, and 3) high inland flooding heights might occur in low risk areas, e.g. rural areas with less potential for property damages.

Impervious surfaces (IRR: 1.37, 95% CI: 1.23, 1.48) and July precipitation (IRR: 1.69, 95% CI: 1.18, 3.28) are the strongest effects, aside from 50-year flooding height, to contribute to the count component of the model. Impervious surfaces are well known for their ability to increase run-off into waterways because they do not allow water to percolate into the ground; it also requires less rain to generate the same amount of run-off [46]. July has some of the most frequent counts of storms events in this study (243), and the events contribute substantially to the monthly precipitation because of the type of precipitation that occurs in the summer in North Carolina. "Pop-up" thunderstorms occur more often in the summertime, and can produce large amounts of precipitation in a localized, short time frame. Up to 72% of total summer rainfall is produced by thunderstorms in the Eastern United States[47]. July and June are also a part of the hurricane season in the Carolinas. Although October has some of the highest number of flooding events in this study time period (274), higher October precipitation leads to lower counts of storms events (IRR: 0.63, 95% CI: 0.37,0.90). Upon further inspection, approximately 50% of these documented events resulted from Hurricane Matthew in 2016. These rare events are difficult to model within monthly 30-year normal precipitation totals. Four of the years included did not have any flooding events that occurred in October.

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[46] Frazer, L. Paving paradise: the peril of impervious surfaces. *Environ. Health Perspect.* **113**, A456–A462 (2005).
[47] Changnon, S. A. & Changnon, D. Long-Term Fluctuations in Thunderstorm Activity in the United States. *Clim. Change* **50**, 489–503 (2001).

Table 3.2.

The incidence rate ratios and odds ratios for the zero inflated Poisson (ZIP) regression models. Confidence intervals were generated from a percentile bootstrap. Only significant effects from the covariates are shown in this table.

	Incidence rate ratios		Odds Ratios
50-year flooding height	2.11 (1.28, 4.61)	50-year flooding height	6.52 (1.35, 72.68)
10-year flooding height	0.59 (0.29, 0.94)	10-year flooding height	0.17 (0.02, 0.59)
Percent impervious surface	1.37 (1.23, 1.48)	May precipitation	2.74 (1.05, 15.06)
July precipitation	1.69 (1.18, 3.28)		
October precipitation	0.63 (0.37, 0.90)		
Monthly precipitation coefficient of variation	0.47 (0.17, 0.96)		

The distribution of flooding events across the state for hydrologic units with available data is shown in Figure 3.3. WNC is highlighted for effect. With the exception of some highly populated areas, most of the central part of the state is predicted to have low to no flooding events. Most of the highest event predictions were either on the coast, in cities, and a few in the WNC region. Nine watersheds were predicted to have more than five flooding events in a decade, including the watershed with the highest number of flooding events (24), Smith Creek in New Hanover County, and a few others that had 10 or more actual flooding events: Masonboro Inlet in New Hanover County and the Headwaters of the South Fork of the New in Watauga County.

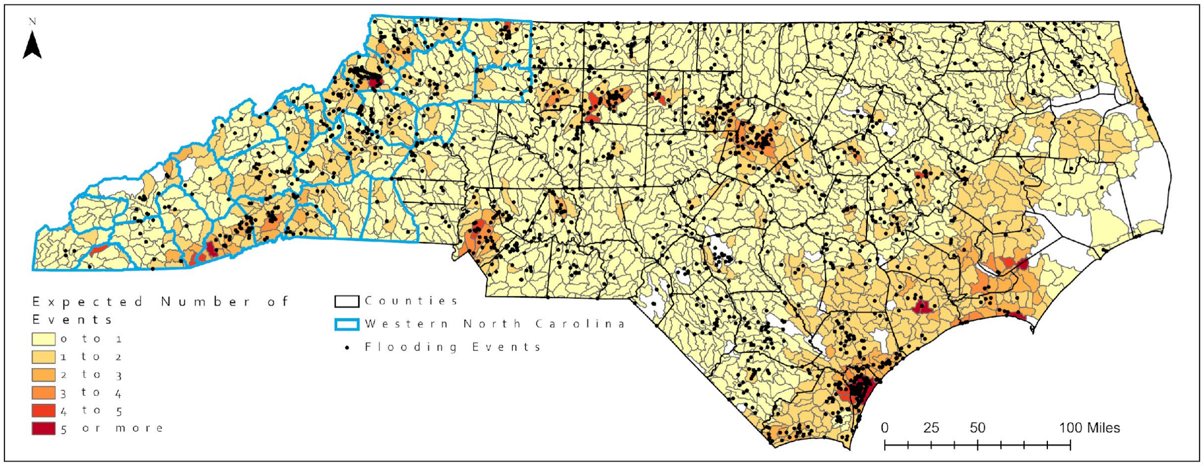


Figure 3.3. *Expected number of flooding events within each watershed based on a bootstrapped aggregated zero-inflated poisson (ZIP) regression model. Documented storm events from the NCEI flooding events database are shown as black dots. Counties are outlined in black and Western North Carolina (WNC) counties are outlined in blue.*

3.7 Analysis of change in future precipitation patterns

Understanding how precipitation changes within watersheds can assist in identifying higher risk time periods for floods and other precipitation related hazards, e.g. droughts, wildfires, and landslides. Although a more robust analysis is needed to conclusively make generalizations concerning precipitation changes, this exploratory analysis is meant to show that climate change projections can be used to make localized inferences.

WorldClim has projected downscaled data on temperature and precipitation from multiple climate models using the four representative concentration pathways (RCP2.6, RCP4.5, RCP6.3, RCP8.5) for two time periods: 2041-2060, and 2061-2080[48]. These are based on the coupled modeling intercomparison project (CMIP) used for the fifth assessment report on climate change from the Intergovernmental Panel on Climate Change (IPCC). Recently (March 2020), the WorldClim group released new downscaled data based for use in the sixth assessment report down to 2.5 arc minutes (~5km^2), but the resolution needed for our analysis has not been released (30 arc seconds, or ~1km^2)[49].

We decided to use the data at 30 arc seconds resolution for monthly precipitation from the Geophysical Fluid Dynamics Laboratory Earth System Model 2 (GFDL-ESM2G) to assess how the precipitation patterns in the state of North Carolina as well as its individual watersheds might change under concentration pathway RCP4.5, which is a more conservative “middle of the road” estimate of future

48 Ibid, N 38
49 Ibid, N 37

climate changes. Much like the historic data from PRISM, we averaged each month's precipitation within a watershed, and calculated relative precipitation change as a percentage change from the 30-year normals to the 2041-2060 period. To incorporate the ANL data, we assumed that the severity of flooding from 10-year and 50-year flood events would increase, and used the 95th percentile values from the process model results as an indicator of this increased severity of flooding in the future.

To further understand the spatial patterns of change in future precipitation patterns, a k-means cluster analysis was performed to see how individual watersheds could be grouped. The NbClust package [50] and visual inspection of clustrees [51] was used to determine the appropriate number of clusters for our analysis. A range of two to 10 clusters was evaluated, and we determined that either two or three clusters were optimal values to use. Three clusters were chosen because of an equal number of indices determining both (two or three clusters) to be the optimal number of clusters, and the increased explanatory power from adding an additional cluster. Sixteen variables were used in the clustering analysis: monthly precipitation change; annual coefficient of variation of monthly precipitation change; changes in flood heights from the 50th to 95th percentile values of flooding height from the 10-year and 50-year flooding events; and the expected current number of flooding events (Section 3.5). Expected number of flooding events were min-max normalized to keep all variables on a similar scale.

3.8 Results of future precipitation analysis

Our findings suggest that watersheds within the state of North Carolina will, on average, see an increase of 39% in the monthly coefficient of variation, and in some months (May and October) may see an average increase of over 30% in monthly precipitation (Figure 1.4). Other notable increases are in June (22%) ad July (26%); we can infer from this that summertime thunderstorms might be either more frequent or more intense, or there will be more frequent days with precipitation in the early summer. This is in line with other studies of the Southern Appalachian Mountains with regards to precipitation patterns in the summer.[52] [53] Other months will see notable decreases in precipitation such as August and September, with decreases of 9% and 12%.

[50] Charrad, M., Ghazzali, N., Boiteau, V. & Niknafs, A. NbClust Package: finding the relevant number of clusters in a dataset. *J. Stat. Softw* (2012).
[51] Kranen, P., Assent, I., Baldauf, C. & Seidl, T. The ClusTree: indexing micro-clusters for anytime stream mining. *Knowl. Inf. Syst.* **29**, 249–272 (2011)
[52] Sugg, J. & Konrad, C. Relating warm season hydroclimatic variability in the southern Appalachians to synoptic weather patterns using self-organizing maps. *Clim. Res.* **74**, 145–160 (2017).
[53] Kinlaw, T., Sugg, J. & Perry, B. Warm Season Hydroclimatic Variability and Change in the Appalachian Region of the Southeastern U.S. from 1950 to 2018. *Atmosphere (Basel).* **10**, 289 (2019)

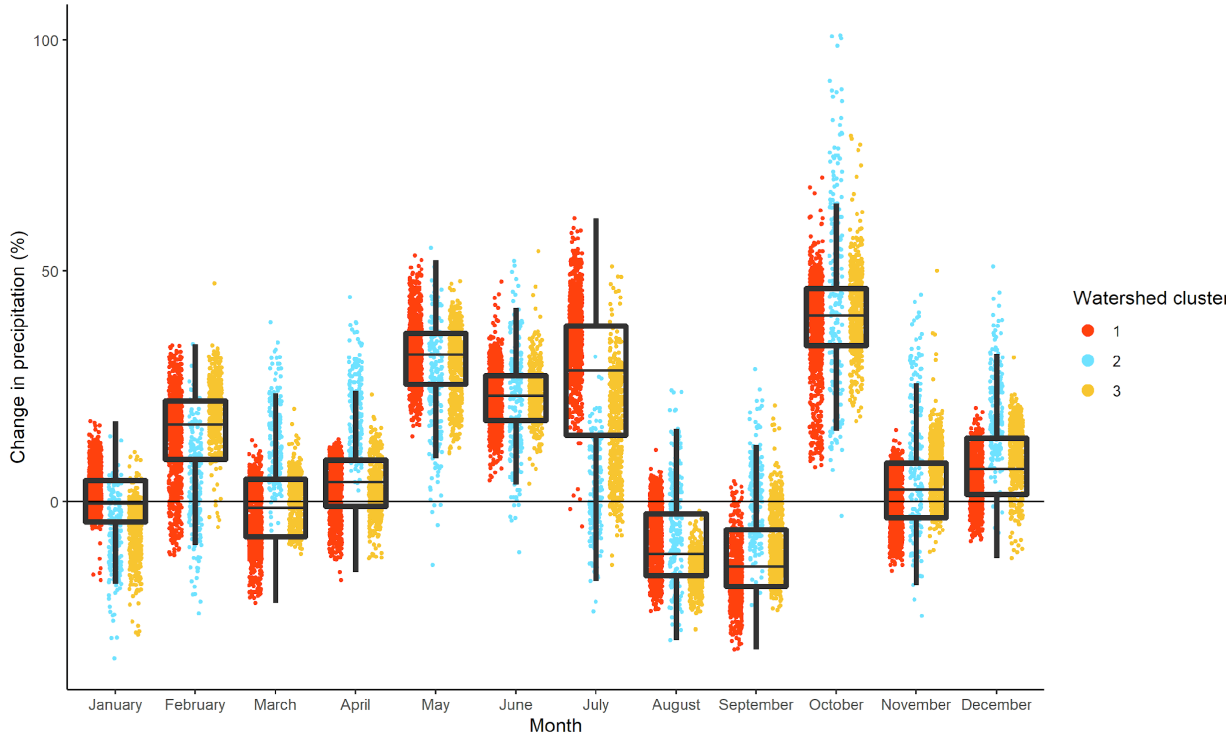


Figure 3.4: *Box and whisker plot of monthly precipitation changes. Median values are represented by the middle line and the box indicates the interquartile range, or the range of the 25th and 75th percentile. Whisker represents values that are 1.5 times the interquartile range. Results from the cluster analysis (Section 1.7) are indicated by three sets of points: red for cluster 1, blue for cluster 2, and yellow for cluster 3.*

The geographic locations of watershed clusters are displayed in Figure 3.5. Cluster 1 generally represents the coastal region with some member watersheds existing in WNC. This group of watersheds is poised to see higher increases in July (36 %) and May (33%) precipitation, but larger decreases in September precipitation (16 %). This set of watersheds is also poised to see a 31% increase in seasonal variability.

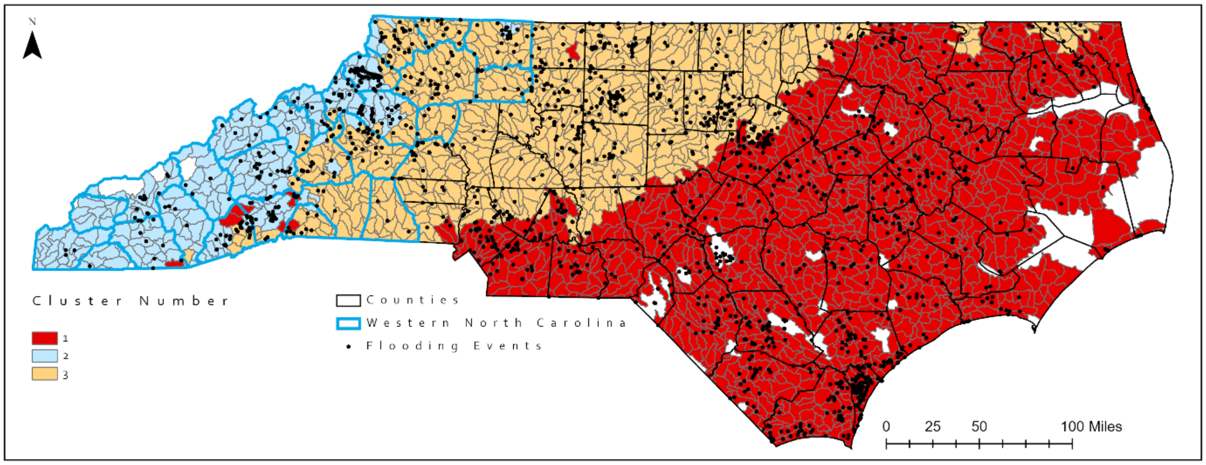


Figure 3.5. *Cluster analysis results for the state of North Carolina. The three clusters following generally the designated regions of North Carolina. Cluster 1 represents the coastal and Eastern part of the state, Cluster 2 represents the Piedmont and many lower elevation components of Western North Carolina (WNC), and Cluster 3 could be described as the most mountainous part of WNC .*

Cluster 2 represents a significant portion of WNC, and this set of watershed is projected to have the lowest changes in 50 year flooding height (23%). A wetter spring is projected for this cluster, with increases of 13% and 20% in March and April Precipitation. Although this cluster had high intracluster variation between precipitation changes in October, this cluster had the highest mean increase in October precipitation (47 %). This is also the cluster with the highest expected number of flooding events. Cluster 3 represents the central, or Piedmont, region of North Carolina with some expanse into the Northeast part of North Carolina. This area is unique in the fact that it has the potential to have the highest increases in 10-year (13 %) and 50-year flooding heights (33 %), February precipitation (20%), and the largest changes in seasonality (66%).

3.9 Landslide Vulnerability

While we did not specifically evaluate the impact on landslide vulnerability as a result of precipitation estimates generated by this analysis, it is worthy to note that landslides are a primary climate-related hazard in WNC due to historical frequency and projections in increasing precipitation at higher elevations[54]. The Appalachian Mountains are a "hotspot" for landslide vulnerability as can be seen in Figure 3.6, and the majority of landslides that occur in North Carolina are in the western region[55]. In addition to the human losses associated with fatalities and injuries, this region incurs a significant economic impact due to uninsurable property losses and delays in business operations (e.g., tourism, transit of goods). For example, the loss in commercial revenues when I-40 was closed for several

[54] North Carolina Department of Environmental Quality (DEQ), 2020: *North Carolina Climate Risk Assessment and Resiliency Report*

[55] Western North Carolina Vitality Index Foundation, *WNC Vitality Index Report, 2016*

months in 2009 was estimated at approximately $1 million per day, and the cost to repair the road was $10.2 million. [56]

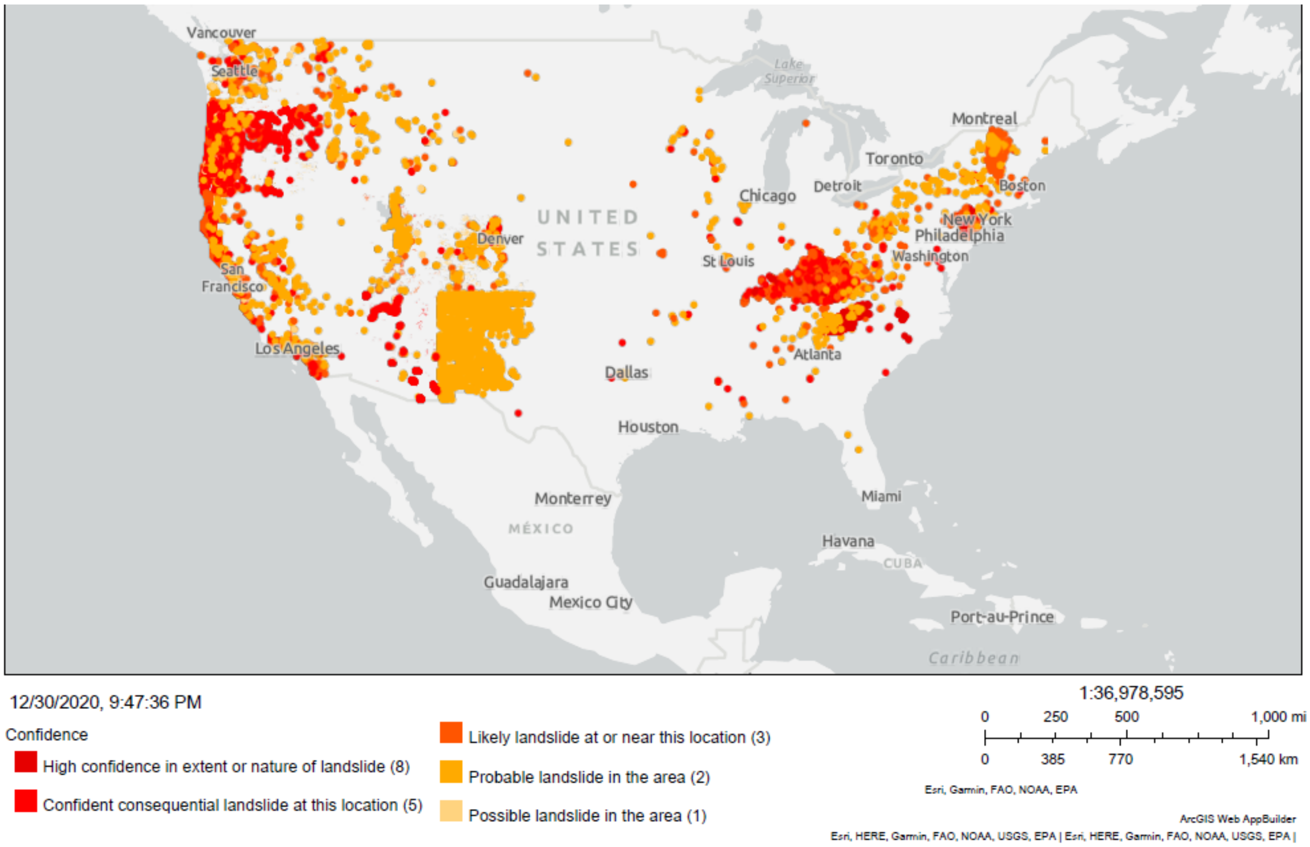


***Figure 3.6**: U.S. Landslide Inventory and Interactive Map, US Geological Survey, Accessed: 12/30/2020.*

3.10 Wildfire Vulnerability

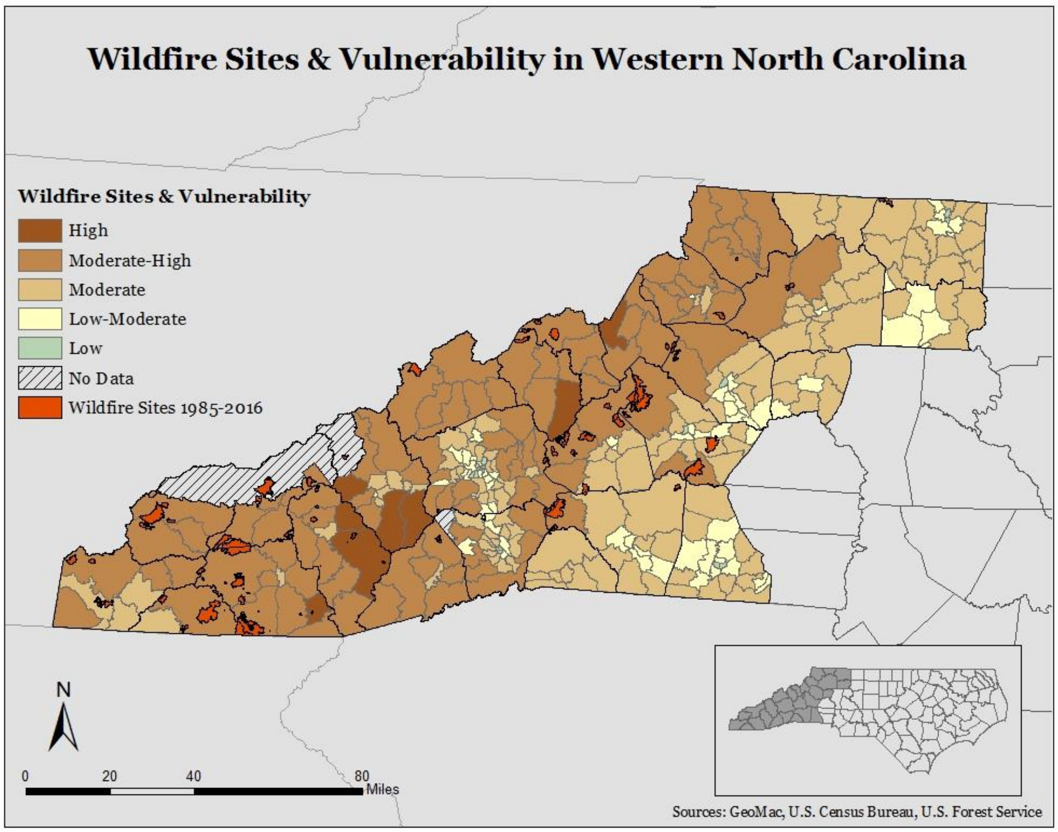
A wildfire occurs in wildland and is described as non-structured rather than prescribed burn[57]. In previous decades, fire suppression has increased the density of vegetation and fire-sensitive species, which can elevate wildfire risk and intensity[58]. Fire suppression in combination with increase in season length, fire size, acreage burned, and developments into the wildland-urban interface has further complicated fire vulnerability and management (USFS 2018a). The increasing threat of destructive wildfires combined with a growing wildland-urban interface resulted in an unprecedented wildfire event

[56] Ibid, N 55

[57] U.S. Forest Service (USFS) (2019) Fire Terminology. https://www.fs.fed.us/nwacfire/home/terminology.html. Accessed 18 Apr 2019

[58] 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

in WNC where nearly 75,000 acres of these counties burned from late October through early December 2016[59]. Recent research in WNC finds that forest cover was the most significant predictor of wildfire, likely because forests present more fuels for wildfire growth. Wildfires were also found to occur in less urban areas with low population densities, which corresponds to previous literature in other locations[60] [61] . Physical vulnerability to wildfire is higher in the southern counties of WNC, with the highest observed in Macon County compared to Buncombe, Watauga, and Caldwell counties. These results highlight that targeted responses are needed particularly for locations most vulnerable to wildfires in a changing climate.



[59] Andersen, L. M. & Sugg, M. M. Geographic multi-criteria evaluation and validation: A case study of wildfire vulnerability in Western North Carolina, USA following the 2016 wildfires. *Int. J. disaster risk Reduct.* **39**, 101123 (2019)
[60] 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
[61] Ibid, N 59

***Figure 3.7**. Figure depicts western NC's vulnerability to wildfire as well as wildfire sites between the years 1985-2016. The Wildfire Vulnerability layer is organized by census tracts, with an overhead layer that depicts WNC county boundaries.*

3.11 Implications for Land Use and Planning

Few studies have tried to explore connections between monthly precipitation and climate impacts at a localized level, but some studies have explored the connections between climate and agriculture. County wide growing season (May-October) precipitation was analyzed for its impacts on crop yields in the Southeastern United States[62]. Across North Carolina, growing season changes were associated positively with yields of soybeans and corn, and the increases in June and July precipitation may increase crop yields for these crops. Other crops like cotton, peanuts, and soybeans could have diminished crops yields because of the large increases in October precipitation. The changes in seasonality that will be experienced by some communities also can cause stress on water resources, and increase likelihood of drought during certain times of the year, especially the months of August and September. Regions of North Carolina that are most sensitive to impacts of drought on agriculture are the coastal and piedmont regions, but some counties in WNC (Alexander, Alleghany, Buncombe, Cleveland, Rutherford, Wilkes) are moderately sensitive to the impacts of drought on their agricultural yields. Although flooding events can also impact crop yields, and can cause significant losses, it is still uncertain the extent to which these events impact agriculture in North Carolina.

Precipitation changes can also influence forests, and as the highest valued crop in the Southeastern United States, could be vulnerable to these changes. Changes in moisture regimes will likely influence forest productivity in the future, and the forests of North Carolina are already some of the most dynamic forests globally, although most of this is from management practices[63] [64]. Species migration has already been shown to be occurring in response to changing precipitation patterns[65]. Additionally, increased warm periods of drought increases the potential for wildfires in forests across North Carolina, which already has frequent occurrence of wildfires from human and natural sources[66].

Changes in the precipitation dynamics also have the potential to influence the occurrence, frequency, and severity of two other natural hazards: Landslides and wildfires. Both total rainfall and intensity affect landslide vulnerability, but at different scales. Total rainfall influences landslide vulnerability at local scales at longer temporal scales, but intensity can affect vulnerability at both local and regional

[62] Eck, M. A., Murray, A. R., Ward, A. R. & Konrad, C. E. Influence of growing season temperature and precipitation anomalies on crop yield in the southeastern United States. *Agric. For. Meteorol.* **291**, 108053 (2020).
[63] Fei, S. *et al.* Divergence of species responses to climate change. *Sci. Adv.* **3**, e1603055 (2017).
[64] Hansen, M. C. *et al.* High-resolution global maps of 21st-century forest cover change. *Science (80-.).* **342**, 850–853 (2013).
[65] McEwan, R. W., Dyer, J. M. & Pederson, N. Multiple interacting ecosystem drivers: toward an encompassing hypothesis of oak forest dynamics across eastern North America. *Ecography (Cop.).* **34**, 244–256 (2011).
[66] Ibid, N59

scales in the short-term[67] . However, forest cover is a stabilizing factor to prevent landslides, so exploring mitigation policies that prevent deforestation in higher risk areas, or reforestation in those areas, can help in reducing the vulnerability to landslides in a changing climate. More research is needed to understand the full scope of climate feedback on landslide vulnerability from a range of climate change scenarios, with a critical analysis of the bias of estimated risks and the underlying uncertainty.

Wildfire risk is increased by changes in climate, especially those areas that are expected to have warmer conditions and an increased length of drought from lack of precipitation. Although difficult to predict the length of future droughts based on the data we used, our findings suggest that the later months of summer might be at increased risk for occurrence of wildfires due to the decreased monthly precipitation in August and September. Although climate can promote conditions in which wildfires have the potential to occur, mitigation of wildfires begins with acknowledge the overwhelming contribution of humans to expanding the season and extent of wildfires in the United States[68] . Forest managers should focus on both minimizing potential exposure through best management practices, but also in educating the public on the dangers of human-induced forest fires and how to prevent them.

Although extreme precipitation events are expected to increase across the Southeastern United States, we cannot project how this changes based on the data we have used. We can, however, suggest that increased summertime precipitation will likely be the results of intense “pop-up” thunderstorms that typically cause flash flooding in smaller, localized watersheds. Analysis of climate models have shown that extreme precipitation events increase during warm periods, and the models may underestimate the future changes in precipitation extremes[69]. Additionally, large-scale changes in circulation are likely to alter the occurrence of different precipitation patterns in Summer mountain storms, with more frequent daily rain at higher elevations and varied patterns in more lowland mountainous regions[70]. Identifying those high watersheds at high risk of exposure to flooding (section 3.5) can guide mitigation efforts to improve flooding resilience such as wetland restoration and protection, revitalization of riparian buffers, limiting development of impervious surfaces in high risk areas, improving dated infrastructure for stormwater, and other risk management and communication strategies. Mitigation now saves money later, and this study helps inform decision making based on watershed storm exposure and potential changes in precipitation regimes with the state of North Carolina.

[67]Gariano, Stefano Luigi, and Fausto Guzzetti. "Landslides in a changing climate." Earth-Science Reviews 162 (2016): 227-252.

[68] Balch, J. K. et al,. Human-started wildfires expand the fire niche across the United States. *Proc. Natl. Acad. Sci.* **114**, 2946 LP – 2951 (2017)

[69] Allan, R. P. & Soden, B. J. Atmospheric Warming and the Amplification of Precipitation Extremes. *Science (80-.).* **321**, 1481 LP – 1484 (2008).

[70] Sugg, J. & Konrad, C. Relating warm season hydroclimatic variability in the southern Appalachians to synoptic weather patterns using self-organizing maps. *Clim. Res.* **74**, 145–160 (2017)

SECTION 4: THE LANDSCAPE OF SOCIOECONOMIC DISPARITIES CONCERNING EXPOSURE, VULNERABILITY, AND RESILIENCE (Objective 2)

4.1 *Climate Change Impacts in Rural Communities*

While much of the discussion around climate vulnerability has centered on coastal communities, there is an increasing focus on rural areas where climate change impacts include those that significantly impact access to basic needs (health, communication, transportation, food/water, shelter), economic well-being, and survival[71]. At the local level, hazard mitigation planning has been the predominant means of addressing climate impacts but mostly as a reactive strategy for extreme weather events. Intentional strategy for building climate resilience is largely absent from local rural planning, and this can be attributed to many reasons, including the lack of awareness of impending impacts, lack of financial resources to implement meaningful proactive strategy, and lack of knowledge on how to build resilience capacity. The recent North Carolina Climate Risk Assessment and Resilience Plan, issued in March 2020, provides a directive and guidance for rural communities to begin integrating considerations for climate vulnerability and adaptation into resilience strategies, predominantly in existing hazard mitigation planning processes[72]. But, there are significant barriers that might prevent building resilience capacity from the standpoint of both natural and human resources[73]. For this project we sought to examine these barriers from the perspective of disparity in social vulnerability in rural regions that can exacerbate the difficulty in building meaningful climate resilience capacity. For this purpose, we needed to first better define the terms "climate vulnerability", "climate resilience", and understand how these are valued using frameworks focused on social vulnerability and community resilience. This section summarizes the work in association with achieving objective 2: *Identify socioeconomic disparities and associated climate vulnerability in rural regions that can inform policy and decision-making*

4.2 Resilience and Social Vulnerability

Using indicator frameworks for assessing disparity in social conditions is helpful in finding correlations and connections in how this disparity can impact both vulnerability to physical climate impacts as well as the capacity for resilience. This information is useful for planning and allocating scarce resources based on greatest need.

A vulnerable community is one in which negative socioeconomic variables contribute to reduction in the community's ability to prepare for, respond to, and recover from hazards. A socially vulnerable community has weak family structures, lack of leadership for decision making and conflict resolution, unequal participation in decision making, weak or no community organizations, and the one in which people are discriminated on racial, ethnic, linguistic or religious basis. Other social factors such as

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[71] Ibid, N 1

[72] Ibid, N54

[73] Lal, Pankaj, Janaki R. R. Alavalapati, and Evan D. Mercer, 2011. "Socio-economic impacts of climate change on rural United States." *Mitigation and Adaptation Strategies for Global Change, 16* (7), 819-844

culture, tradition, religion, local norms and values, economic standard, and political accountability also play a vital role determining the social vulnerability of a community[74] .

A resilient community is one that has the available resources to respond, to withstand, and to recover from adverse situations; but also the capacity to adapt, to anticipate, and to potentially prevent catastrophic events from occurring[75] [76]. Resilience is a characteristic of the demographics of the population, the stability of social networks, the structure and diversity of the economy, and the institutional capacity to enact policies that foster resilience[77]

Resilience and vulnerability are challenging constructs to analyze scientifically. A plethora of frameworks, indicators, and metrics exist that attempt to quantify these constructs, yet agreement on what constitutes a consistent set of metrics to evaluate both resilience and vulnerability is lacking [78]. The conversation surrounding composite indicators can be contentious, but there is an active need to explore how best to use resilience and vulnerability indicators. Through this aspect of our project, we want to explore a few vulnerability and resilience indicators, and how these qualities of a community are distributed across North Carolina.

4.3 Social Vulnerability Indicators

4.3.1 Social Determinants of Health (SDoH)

Social Determinants of Health (SDoH) encompass the circumstances of all individuals, including upbringing, working, community conditions, socioeconomic status, education, employment, and an individual's access to community and health services.[79] More broadly, SDoH are factors in the social environment that contribute to or detract individuals' and communities' health. Understanding data on social determinants of health, such as income, educational level, and employment can help focus efforts to improve community health and improve understanding of the differential vulnerability from environmental hazards. The authors compiled over 100 variables from multiple sources to quantify the SDoH at the census-tract level (See Table A.2 in Appendix). After consultation with planners, public health personnel and geographers, a total of 60 variables were used in the final analysis. Principal component analysis (PCA) was used to reduce multicollinearity and create components for SDoH mapping and resulted in 15 components (Table 4.1). Each component was added using an equal-weight

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[74] Binita KC, Shepherd, JM; Johnson Gaither, C. (2015) Climate change vulnerability assessment in Georgia. *Applied Geography, Volume 62*, P 62-74

[75] Cutter, S. L., Burton, C. G. & Emrich, C. T. Disaster resilience indicators for benchmarking baseline conditions. *J. Homel. Secur. Emerg. Manag.* **7**, (2010)

[76] Cutter, S. L. The landscape of disaster resilience indicators in the USA. *Nat. hazards* **80**, 741–758 (2016).

[77] Ristino, L. (2019). Surviving Climate Change in America: Toward a Rural Resilience Framework. *W. New Eng. L. Rev.*, *41*, 521

[78] Summers, J. Kevin, Linda C. Harwell, Lisa M. Smith, and Kyle D. Buck, 2017. "Measuring community resilience to natural hazards: Natural Hazard Resilience Screening Index—Development and application to the United States." *Landscape and Urban Planning 158,* 75-86

[79] Artiga, Samantha, and Elizabeth Hinton. "Beyond health care: the role of social determinants in promoting health and health equity." *Health* 20.10 (2019): 1-13

framework to the Geographic Information System (GIS) to create a final map of SDoH vulnerability (Figure 4.1).

Table 4.1.

Principal Component Analysis 2 - Components for SDoH

Component Number	Cardinality	Component Name	Variance*	Top 5 Dominant Variables
1	+	Poverty	16.511	● FIn_BPov - Families Income Below Poverty ● FHH_NoHusb - Female Householder ● PerPopBPov - Population with Poverty Status, % Below Poverty ● PopBlack - African American Population ● ChU18LivSP - Children Under 18 Single Parent
2	+	Over 65 Age	12.620	● PopNoLabFo - Population Not in Labor Force ● PopCvEmp - Labor Force, Civilian Employed ● TPop65Over - Total Population 65 and Older ● FPop65Over - Female Population 65 and Older ● MPop65Over - Male Population 65 and Older
3	-	Mobile Home Housing	10.640	● Hospitals - Count of Hospitals ● HousMobHom - Mobile Home Housing Units ● OHMobHome - Occupied Housing Mobile Homes ● Pop_ColBac - Population with College Education, Bachelor's Degree ● Pop_HighEd - Population with a Master's Degree, Doctorate Degree, or Professional School Degree
4	-	Public (Use) Facilities	8.222	● Worship - Count of Places of Worship ● Pharmacies - Count of Pharmacies ● Banks - Count of Banks ● TPopUnd18 - Total Population Under 18 ● WrkDA_Cp - Drive alone or Carpool (Workers)
5	-	Employment	4.741	● Pop_ArmFor - Population in Armed Forces ● WrkB_W - Bike or Walk ● PopCvEmp - Population in Labor Force, Civilian Employed ● CvPopEmp - Civilian Population Employed ● PHH_OneVeh - Households with One Vehicle
6	+	Over 65	3.410	● FPop65Over - Female Population 65 and Over ● PopNoLabFo - Population Not in Labor Force ● TPop65Over - Total Population 65 and Over ● OcH_Rchild - Occupied Housing with Children Under 18 ● PopCvEmp - Population in Labor Force, Civilian Employed
7	+	Mental Health Facilities	3.070	● MH_Count - Mental Health Facilities ● PC_Count - Primary Care Facilities ● TPopUnder5 - Total Population Under 5 Years ● Pop_ArmFor - Population in Armed Forces ● MPopUnder5 - Male Population Under 5 years
8	+	Under 5 Age	2.872	● TPopUnder5 - Total Population Under 5 Years ● MPopUnder5 - Male Population under 5 Years ● FPopUnder5 - Female Population Under 5 Years ● GasStation - Count of Gas Stations ● NursHome - Count of Nursing Home

9	+	Primary Care Facilities	2.424	• PC_Count - Primary Care Facilities • MH_Count - Mental Health Facilities • AvgRHHSize - Average Renter Household Size • PopOthRace - Population that is some other race alone • AvgHHSize - Average Household Size
10	+	Population Under 18	2.245	• GasStation - Count of Gas Stations • TPopUnd18 - Total Population Under 18 Years • MGR_HHInc - Median Gross Rent as % of Household Income • FPopUnd18 - Female Population Under 18 Years • MPopUnd18 - Male Population Under 18 Years
11	-	Education	1.905	• College - Count of Colleges • PopAmInd - Population American Indian or Alaskan Native • MobHome - Count of Mobile Homes • PrivSchools - Count of Private Schools • HousMobHom - Housing Units Mobile Home
12	-	Public (Health) Facilities	1.750	• Libraries - Count of Libraries • PopHawaii - Population Hawaii or Pacific Islander • PubHlthDep - Count of Public Health Departments • PopTwoRace - Population Two or More Races • NursHome - Count of Nursing Homes
13	+	Urgent Care Facilities	1.702	• UrgentCare - Count of Urgent Care Facilities • PopAmInd - Population American Indian or Alaskan Native • MGR_HHInc - Median Gross Rent as % of Household Income • TPopUnd18 - Total Population Under 18 • PopTwoRace - Population Two or More Races
14	+	Race	1.622	• PopAsian - Population Asian • Libraries - Count of Public Libraries • MGR_HHInc - Median Gross Rent as % of Household Income • PopOthRace - Population Other Race • WrkPT - Public Transportation (Workers)
15	+	Public (Station) Facilities	1.607	• FireStat - Count of Fire Stations • PopAmInd - Population American Indian or Alaskan Native • MobHome - Count of Mobile Homes • PopBlack - Population African American • GasStation - Count of Gas Stations
16	+	College	1.564	• College - Count of Colleges • PopAmInd - Population American Indian or Alaskan Native • MGR_HHInc - Median Gross Rent as % of Household Income • PubHlthDep - Count of Public Health Departments • PopBlack - Population African American
* Variance is found from the Total Variance Explained table from the PCA output from SPSS - column name Initial Eigenvalues, % of Variance				

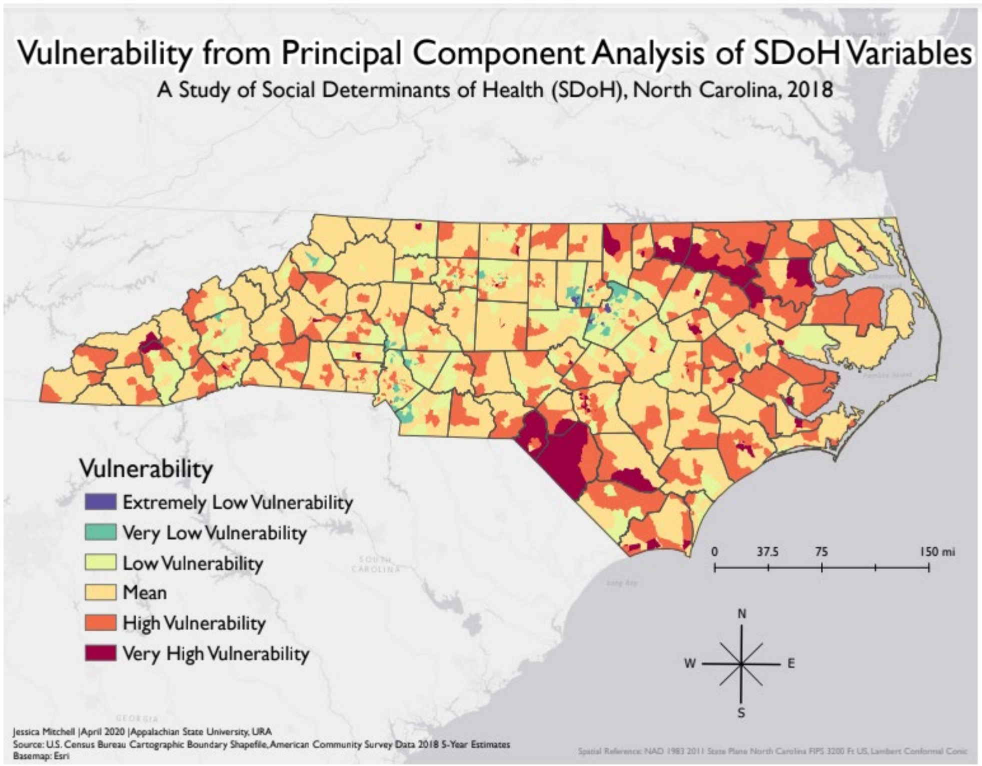

Figure 4.1*: Map of the Social Determinant of Health (SDoH) for North Carolina based on a 2018 analysis of data. Data from 60 variables was orthogonalized using Principal Components Analysis into 16 significant components. These were standardized and classified into 5 categories based on quantiles.*

4.3.2 SoVI®

The *SoVI®* is a measure of underlying social vulnerability to hazard, and provides a comparative metric to measure the capacity for preparedness and response at the county level. In this report, authors replicated *SoVI®*methods to examine underlying vulnerability at the census-tract level. 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. 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). Components with eigenvalues greater than one were retained, leaving seven components. 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.

4.3.3 CDC's Social Vulnerability Index (SVI)

Like SoVI, the Center for Disease Controls (CDC)'s Social Vulnerability Index (SVI) measures communities' resilience when exposed to external stresses like disease outbreaks, natural and/or human-caused disasters. The CDC's SVI uses 15 U.S. Census variables to determine vulnerability, including poverty, lack of vehicle access, and crowded housing and groups them into four-related themes. More specifically the CDC's SVI includes the following variables: Below Poverty, Unemployed, Income, No High School Diploma, Aged 64 and older, Aged 17 or younger, Older than Age 5 with a disability, single-parent households, minority, speak English "less than well", multi-unit structures, mobile homes, crowding, no vehicle, group quarters.

4.4 Climate Resilience Indicators

4.4.1 Natural Hazards Resilience Screening Index NaHRSI (Formerly CRSI)

The Natural Hazards resilience screening index (NaHRSI), formerly the Climate Resilience Screening Index (CRSI), was developed by the United States Environmental Protection Agency (EPA) as a tool for communities to evaluate their vulnerability and resilience to acute natural hazards. For this project, we will refer to this as the original acronym CRSI. The CRSI is based on publicly available data. Its primary purpose is to inform decision-makers on the characteristics that make a community resilient and target potential areas of improvement. The development of the CRSI starts with a recognition that vulnerability and recovery sit on a spectrum of resilience. This metric can be loosely defined as the ratio between the governance, or the planning, regulation, and training that a community executes, and the inherent risk of exposure to natural hazards. Governance is also determined by the community's social structure, the natural environment, and the built environment.

The resilience literature was surveyed and analyzed for features aligned with the EPA's notions of resilience to develop the composite index of the CRSI. Although the ideas generally align in the discussion of community resilience, the application is different depending on field, expertise, and focus. The CRSI uses five domains (risk, governance, society, built environment, and natural environment) with 28 indicators and 117 submetrics for their index. Variables were normalized as needed and standardized using min-max scaling.

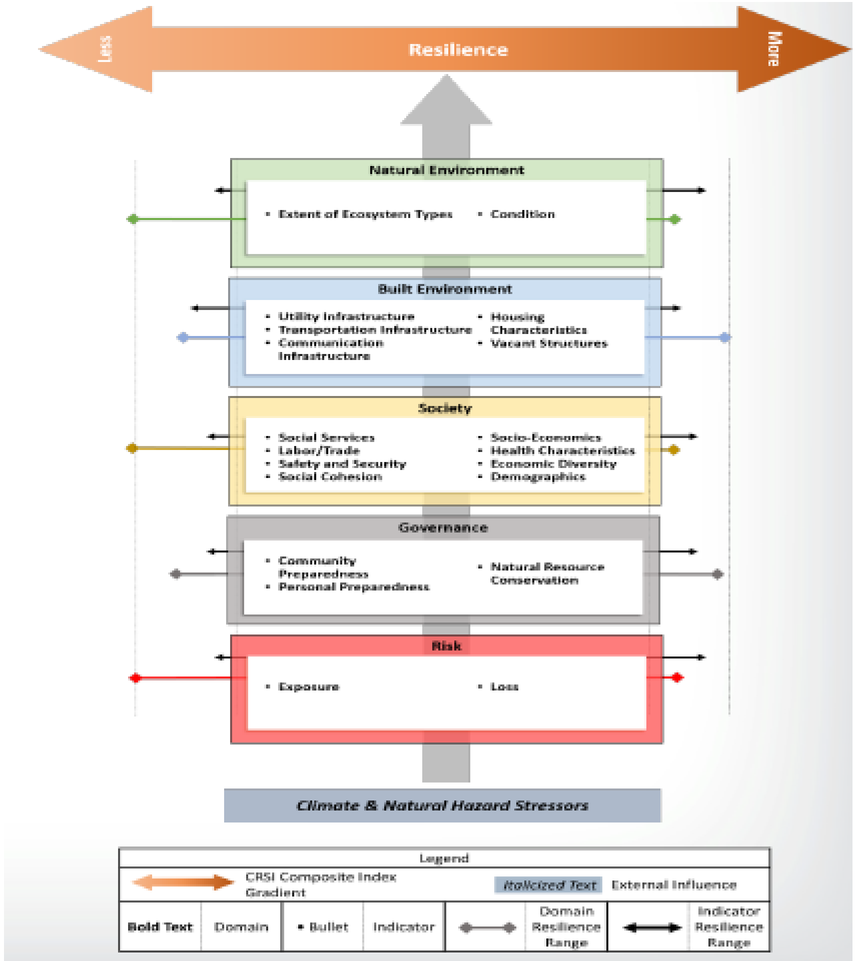

Figure 4.2 - *Climate Resilience Screening Index (CRSI) - Domains of Resilience. Source: Figure from Summers et al. 2017*

The unique aspect of the CRSI is the incorporation of a risk domain in the calculation of 12 natural hazards and five technological hazards, e.g. locations of superfund sites, toxic release sites. The risk domain is calculated using a multi-hazard risk assessment approach which assesses exposure in a geographically context. This exposure is combined with natural, crop, or life and property losses to calculate the risk associated with each land use type (natural, dual-use, or developed). These are summed to get a county level comprehensive assessment of risk, described as the probability that a type of land will be exposed to a hazard that results in losses of property, life, crops, or in natural lands. These were min-max scaled similar to the other domains.

The final calculation involves starting with the base assumption that resilience is the ratio of the recoverability (governance) and the vulnerability (risk). This is referred to as the basic resilience. Basic resilience is adjusted with multipliers for each of the remaining domains. The multipliers for the society, built environment, and natural environment are scaled by calculating the difference between a county's domain scores and the median score, and dividing this by the median score for a specific domain. The final CRSI scores is calculated using the equation below:

$$CRSI_i = \frac{Gov_i\,(1+ Soc(a)_i + BE(a)_i + NE(a)_i)}{Risk_i}$$

Where CRSI is the resilience score for county i, is the governance domain score, is the society domain multiplier, is the built environment multiplier, is the natural environment multiplier, and is the risk domain score.

4.4.2 Building Resilient Infrastructure and Communities (BRIC)

Cutter et al. (2014) describe the disaster resilience literature as "mired in definitional debates, epistemological orientations of researchers, and differences in basic approaches to measurement." Their empirically based matrix Baseline resilience indicators for Communities (BRIC) combines conceptual and theoretical clarity with policy relevance and ease of application. The tool uses a common set of freely accessible variables to assess resilience, at the county level, across six domains (or capitals) from the literature: social, economic, housing and infrastructure, institutional, community, and environmental. They found highest resilience in counties in the Midwest and Great Plains, and lowest values in the West, the Appalachians, and along the US-Mexico border. They note that "inherent resilience is not the opposite of social vulnerability, but a distinctly different construct both conceptually and empirically." The BRIC tool highlights urban/rural differences [80]: "Resilience in urban areas is primarily driven by economic capital, whereas community capital is the most important driver of disaster resilience in rural areas," the latter also showing spatial variability, such that resilience-building efforts must be sensitive to local context rather than using a one-size-fits-all approach.

4.4.3 Comparison of the CRSI and BRIC in North Carolina

One of the issues with indicators metrics such as CRSI and the BRIC is that the scores depend highly on the background of the developing group, the selection of variables, and the aggregation techniques to arrive at a final indication score. Although the CRSI and the BRIC have similar approaches and time periods of analysis, the correlation between the scores per county are weak within the state of North Carolina (Kendall's Tau=-0.0929, p=.171). Part of this can be attributed to the fact that the BRIC does not include a risk of natural hazards component, but even removing this factor from the CRSI, the correlation between these estimates is not significant (Tau=.132, p=0.052). This is not to say that these measures are not informative, but rather there is a valid reason for the contentious debate about their efficacy. An indicator created by a group with a more ecological framework of resilience will approach the weighting and variables selection with a different lens than a social scientist or a geographer. That doesn't mean they are not useful for comparison, but decision-makers need to be informed concerning the foci, boundary conditions, and theoretical framework of the resilience indicator used.

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[80] Ibid, N 28

The core idea of the BRIC and the CRSI are the same, and many of the domains are similar. They both can be used to compare places across the United States, determine specific drivers of resilience, and with periodic updates evaluate improvements in resilience capacity over time. The BRIC's selection of variables is evaluated to make sure that within each domain there is uniqueness within the selection of metrics within each domain, and that the domains do not show much correlation. This evaluation of metrics within the CRSI is not discussed in the literature, however. The number of metrics used in the BRIC is also much smaller than the CRSI, but there is some overlap between the selected variables. However there is one primary difference that probably justifies the poor correlations between the two. The BRIC uses a summing approach to create the composite BRIC scores from the six resilience domains, whereas the CRSI is a governance score that is a weighted sum of itself and the multiplier mentioned in the equation above. Because of these differences, we decide to use both to evaluate differences in perceived baseline resilience with Western North Carolina and the rest of the state.

4.5 Analysis of Rural Western North Carolina's Climate Resilience

4.5.1 Comparison of Western North Carolina's resilience

We desired to examine further differences between rural Western North Carolina and the rest of the state. Using the designation of WNC counties from Andersen and Sugg 2019 and the county-level rural-urban continuum codes from the United States department of agriculture, we identified 20 counties within North Carolina that would fit a technical description of rural WNC. Using a nonparametric Kruskal-wallis test, we evaluated differences in the domain scores in the CRSI and BRIC. Within the CRSI, rural WNC is unique in terms of having lower governance ($p<0.01$) and built environment ($p=0.020$) scores, but higher social domain ($p=0.024$) scores. Because the nature of the weighting of governance scores in the CRSI, rural WNC also exhibited significantly lower ($p<0.01$) CRSI final scores. Within the BRIC, rural WNC had significantly lower economic, institutional, and overall BRIC scores ($p<0.01$)

To evaluate the cluster of high resilience, low resilience, outliers, we explored the significantly different domains and the composite scores of the BRIC and CRSI using the local indicators of a spatial autocorrelation (LISA) analysis.

4.5.2 Local indicators of spatial autocorrelation (LISA) Analysis

As a part of the AT&T Grant task list for objective 2, a LISA analysis for CRSI scores and BRIC scores across the state of North Carolina was conducted using ArcMap 10.4. After beginning with the overall scores themselves, the analysis also included subdomains from each score. For CRSI, the subdomains that are included in the analysis are governance, built environment, and society, whereas for BRIC, the additional subdomains included are economic and institutional resilience. The spatial analysis for both scores was conducted across the state of North Carolina.

To assess spatial autocorrelation at the local level, We used the cluster and outlier analysis (Anselin Local Moran's I) in ArcMap 10.5. The unit of analysis was county resilience scores, and we conceived spatial relationships based on contiguity edges only. This specific analysis technique is effective when polygons are similar in size and distribution, and when spatial relationships are a result of this polygon proximity. Because polygon continuity was used for the conceptualization of spatial relationships, row standardization was applied in order to mitigate bias due to polygon features having differing numbers of neighbors.

4.5.3 Results of LISA analysis

For the overall CRSI score analysis, there is a prominent Low-Low cluster located throughout much of the north/central western region of the state, encompassing the counties of Watauga* and Caldwell* (which are both part of the AT&T case study area), as well as counties located on the southern NC/SC border, such as Rutherford county (Figure 4.3) Overall, the cluster is made up of 16 counties and signifies this sub-region as having low CRSI score values relative to the mean, representing a lower overall resilience to acute weather events.

For the governance subdomain, there is a significant Low-Low cluster located across the majority of the western region of the state, starting with Watuaga* and Caldwell* county in the north/central western portion of the state, and moving southeast. Noticeably, there is also one county polygon, Madison county, that is surrounded by the Low-Low cluster, but is rather identified as a High-Low outlier. This signifies that Madison county has a high governance-resiliency score and is surrounded by low-resiliency values, making it an outlier in WNC for this specific subdomain. For the CRSI built environment subdomain analysis, the only statistically significant cluster identified in WNC is a Low-Low cluster and encompasses only Cherokee county. Lastly, for CRSI's society structure subdomain, there is a High-High cluster located in south-west WNC, encompassing eight counties (Yancey, Buncombe*, Madison, Henderson, Transylvania, Jackson, Macon*, and Haywood). There are also two Low-High outliers identified in WNC, Rutherford county and Graham* county. These results signify a statistically significant cluster of high-societal resilience values, along with two county outliers that have low societal-resilience, but are surrounded by high scores.

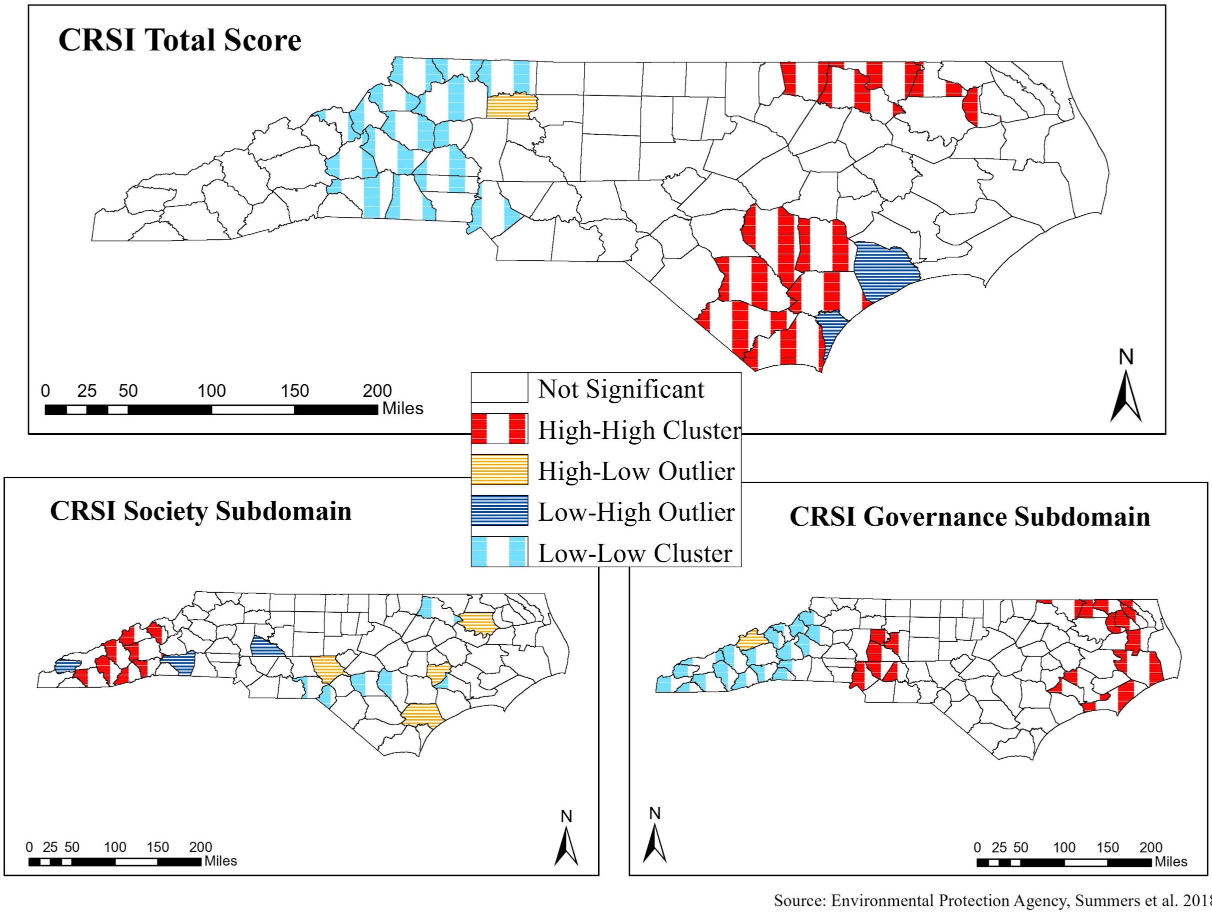
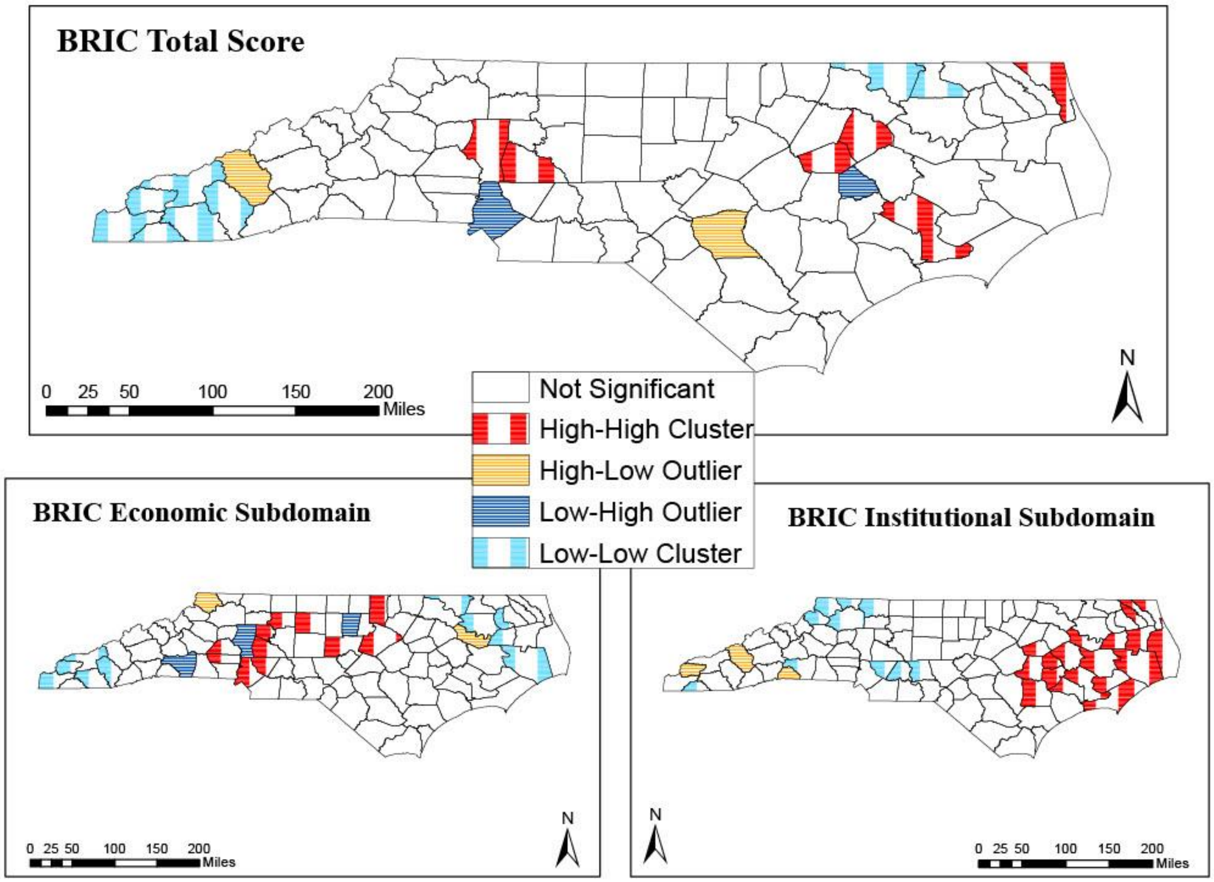


Figure 4.3. *Mapping the LISA (Local's Moran I) across the United States for spatial clustering of CRSI scores. Clustering were identified into two groups, high-high and low-low cluster, and outliers within each of these grouping are also shown. Significance level was 0.05.*

The analysis for the BRIC scores and its respective subdomains were also examined in the scope of WNC Figure 4.4). In terms of the overall BRIC score output, there is a Low-Low cluster located on the western-most portion of the state enveloping six counties: Swain, Jackson, Macon*, Clay, Cherokee, and Graham*. Additionally, Haywood county is identified as a High-Low outlier. These results indicate that the westernmost portion of the state has low BRIC values relative to the mean, representing low-overall community resilience, with the exception of Haywood county, which has a high resiliency value but is surrounded by the low-value cluster. For the BRIC Economic subdomain, there is also a Low-Low cluster encompassing the majority of the westernmost portion of the state, including the counties of Swain, Jackson, Macon*, Cherokee, and Graham*. Additionally, two High-Low outliers are identified near WNC, including Rutherford county and Ashe county. This domain analysis signifies the westernmost portion of the state as having a low overall economic resilience score, with the exception of the two outlier counties that have a high economic resilience scoring, but are surrounded by low values (See Figure 4.4)



Source: Hazard Vulnerability and Research Institute, University of South Carolina, 2020

Figure 4.4. *Mapping the LISA (Local's Moran I) across the United States for spatial clustering of CRSI scores. Clustering were identified into two groups, high-high and low-low cluster, and outliers within each of these grouping are also shown. Significance level was 0.05.*

Lastly, for the Institutional resilience BRIC domain there are three different Low-Low clusters identified in WNC, as well as three High-Low outliers. Beginning with the cluster located along the NW portion of the state (along the NC-VA border), this cluster encompasses five NC counties: Surry, Alleghany, Ashe, Wilkes, and Watauga*. Additionally, there are two Low-Low clusters, both encompassing only one county, identified as Rutherford county and Clay County (both SW). Lastly, three High-Low outliers are identified as Polk, Haywood, and Graham* county. These results indicate the presence of three statistically significant low institutional resilience clusters, along with three counties identified as exceptions, due to their high institutional-resilience scores surrounded by low values.

The results of this analysis indicate that overall, the western region of North Carolina is composed of counties characterized by significant clusters of low resilience scores. The exception for this general trend is seen through the CRSI society subdomain, which features a statistically significant high resiliency cluster (including both Buncombe* and Macon* county); however, this subdomain also includes two outliers characterized by low societal resilience (Rutherford and Graham* county). Overall, this subdomain was the only output throughout this analysis that identified a high resiliency cluster, further proving that in general, WNC is characterized as having low community resilience to climate change and acute weather events.

*- counties included in the AT&T case study area (Buncombe, Caldwell, Graham, Macon, Watauga)

4.6 Interaction of Social Vulnerability and Physical Exposure to Hazards

To better demonstrate the importance of examining hazard risk exposure through a lens of social vulnerability, this section provides an analysis for two different prominent hazards in WNC: Wildfires and landslides. Using the mapping of social vulnerability, we overlaid the physical exposure to these events to highlight areas where greater priority exists for building resilience in these communities.

4.6.1 Social vulnerability and Wildfire exposure

Future climate change and human development are expected to expand the wildlife-urban interface, alter precipitation, and stress water resources in the region, which may lead to more frequent wildfire events. In 2016, WNC had an unprecedented wildfire event with nearly 75,000 acres burned across the entire area. Using previous wildfire events from 1985 to 2016, a wildfire vulnerability index was created through multi-criteria evaluation that included elevation aspect, biomass, elevation, hillshade, forest cover, precipitation, population density, road density, slope and temperature. Variables were selected and weighted based on regression analysis and analytical hierarchical processing to reduce subjectivity (Figure 4.4.1).

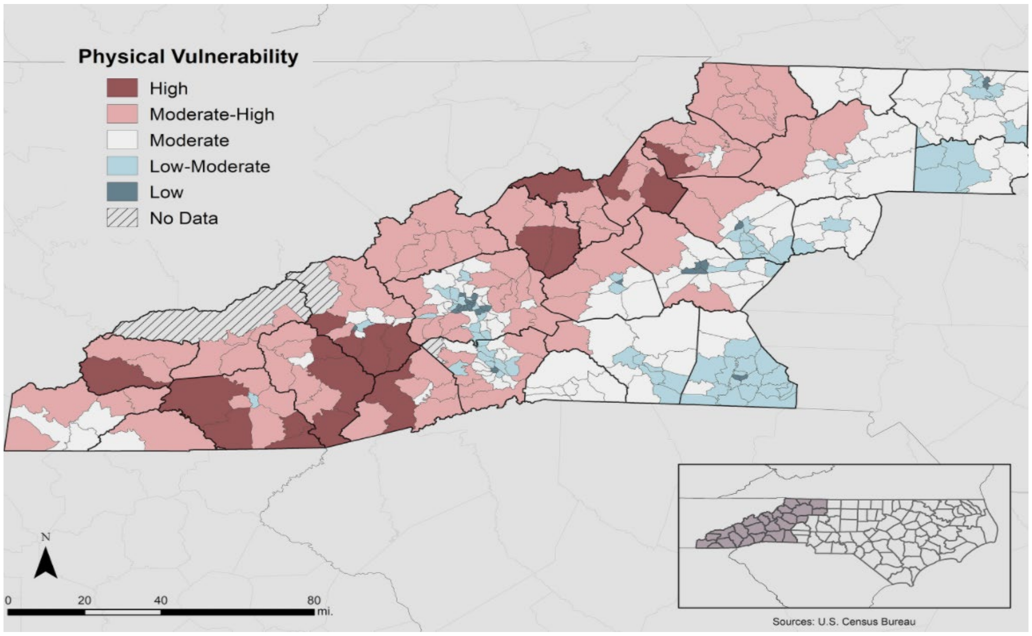


Figure 4.4.1 *Physical vulnerability to wildfire at the census-tract level for western North Carolina. Classification is standard deviation with high indicating the highest wildfire risk and low indicting the lowest wildfire risk.*

The underlying social vulnerability of the communities to wildfire was calculated using the well-established method of Cutter 2003, to calculate SoVI using principal component analysis. Both indices were combined and displayed using bivariate mapping techniques to assess where social and physical vulnerability to wildfire coincide in western North Carolina. Index results were validated using 2016 wildfire events and were robust in predicting wildfire occurrence and spread. Further details can be found in Andersen and Sugg 2019[81]. These maps are shown in Figure 4.4.2 and 4.4.3

[81] Ibid, N 38

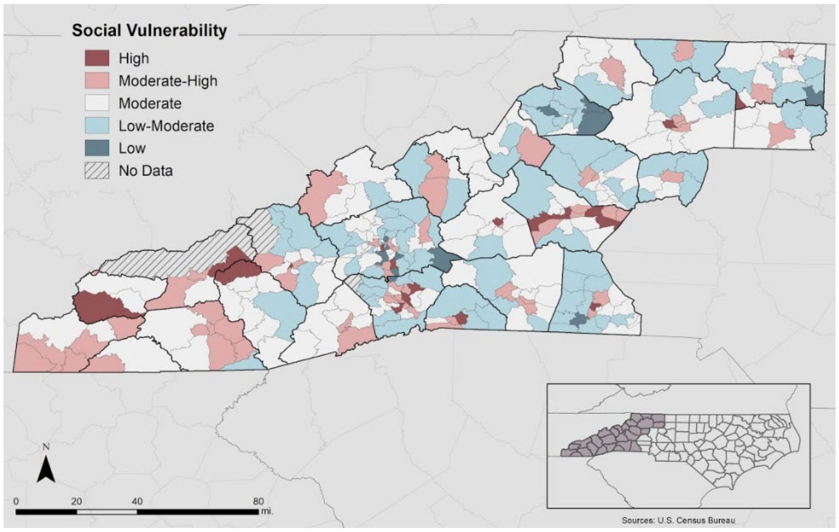


Figure 4.4.2*: Social Vulnerability of Western North Carolina counties using the SoVI methodology* (Andersen and Sugg 2019).

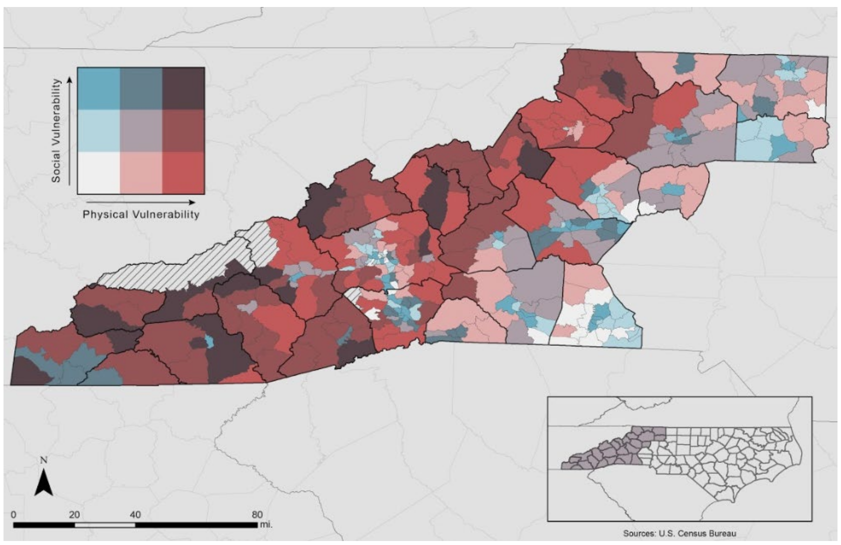


Figure 4.4.3*: Social Vulnerability and Physical Vulnerability of Western North Carolina counties using the SoVI methodology and validated index of physical wildfire vulnerability* (Andersen and Sugg 2019).

4.7.2 Social Vulnerability and Landslide Exposure

As previously mentioned, landslide vulnerability is a primary hazard concern in several parts of Western North Carolina. Figure 4.6 shows known landslide events in WNC through June 2011. The most common and widespread type of landslide are mudslides (debris flows), and the concentration of these appear to be in the counties of Watauga (northern part), Buncombe and Haywood (central area), and Macon (southern area). It is worthy to mention that these counties house relatively developed regions of WNC, where greater resilience planning as it applies to land restoration would be beneficial. In Boone, NC (Watauga County) for example, "steep slope" building restrictions have been enacted as a means of preventing development in areas most vulnerable to landslides[82] .

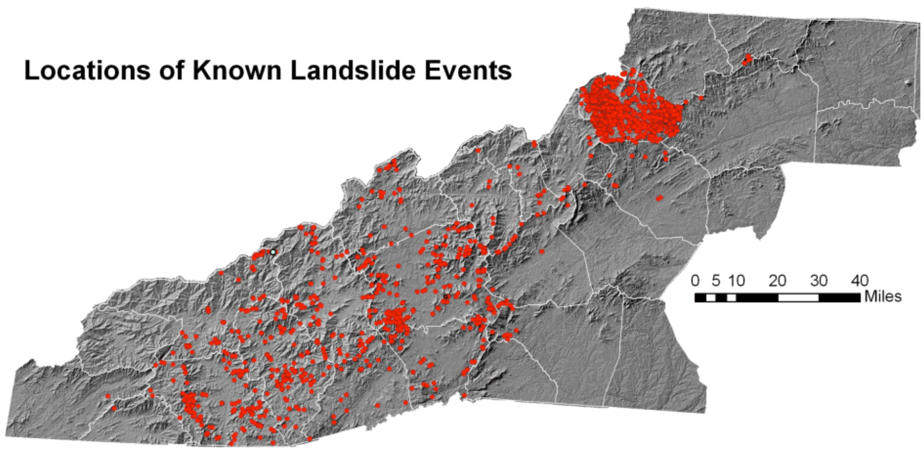


Figure 4.6 *- Known landslide events through June 2011 (3,290 events). The highest concentration in Watauga county occurred in August, 1940 (over 2,000). Source: Western NC Vitality Index Report 2016.*

The NC Climate Risk Assessment and Resilience Report provides a map for potentially underserved populations in areas with historic exposure to landslides (Figure 4.7). As compared to the historic occurrence of wildfires, landslide events are concentrated in the western part of the state. There are several regions, particularly in the southwestern part of the state, where the most socially vulnerable are at the greatest risk for physical and economic loss associated with landslides. Potential for increasing precipitation and failure to plan for building resilience could exacerbate these losses.

[82] Unified Development Ordinance, Town of Boone, 2014

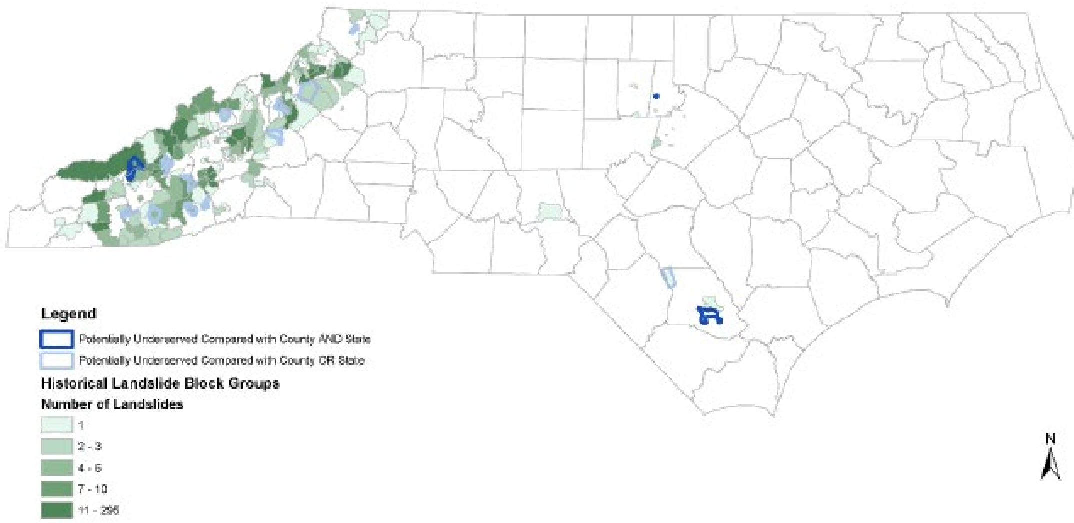


***Figure 4.7**: Potentially Underserved Populations in Historic Landslide Areas in North Carolina (Source: NC Climate Risk Assessment and Resilience Plan, 2020)*

It is relevant to note that, in the Hazard Mitigation Plans evaluated for the Case Study in the next section, landslides are generally rated with higher risk than wildfires; this is also noted in Table 4.2, which identifies the primary "climate stressors" in the various Prosperity Zones across North Carolina[83]. In all 3 of the prosperity zones in the western part of the state, landslides are one of (and in some cases the only) climate stressor that impacts the economic condition of that region. This is of particular concern because of the reliance on natural resources and land use in these regions for agriculture, forest products, and tourism, as well as transit of goods. This can also have an impact on disaster response and consequently impacts climate resilience in rural communities. As mentioned in the Literature Review, the economic condition of business and industry in rural regions is crucial to the ability to build resilience capacity; consequently, additional research like that done by Anderson and Sugg (2019) for wildfire vulnerability would be beneficial for WNC, given the concentration of landslides in this area and variance in social vulnerability illustrated above.

[83] NC Climate Risk Assessment and Resilience Plan, North Carolina Department of Environmental Quality, 2020

Table 4.2

Climate stressors in Prosperity Zones -- NW and Western (NC Climate Risk Assessment Report)

Assets, Regulations, Services	Extreme Heat	Flooding (River and Land)	Water Shortage (Drought)	Changed Seasons	Landslides	Saltwater Intrusion	Storm Surge	Tidal Flooding	Wildfire	Dam Failure
Division of Employment Security		*								
NC Seafood Industrial Park Authority (Wanchese, Engelhard)		*				*	*	*		
Division of Workforce Solutions		*								
Prosperity Zones										
North Central Prosperity Zone		*								
Northeast Prosperity Zone						*	*	*		
Northwest Prosperity Zone					*					
Piedmont Triad Prosperity Zone		*								
Sandhills Prosperity Zone		*	*							
Southeast Prosperity Zone		*				*	*	*		
Southwest Prosperity Zone					*					
Western Prosperity Zone					*				*	
Regional Planning Offices										
Southeast Regional Planning Office						*	*	*		
Western Regional Planning Office					*				*	

SECTION 5: CASE STUDY OF RESILIENCE AND VULNERABILITY OF SELECTED COUNTIES

5.1 Diversity of resilience and vulnerability within Western North Carolina

While WNC and its rural portions can be distinguished from the rest of the state using these national-level indicators of resilience, we wanted to investigate the concepts of resilience and vulnerability at a finer scale. We selected five counties in WNC that spanned the spectrum of the urban-rural continuum codes; the five counties selected are Buncombe, Caldwell, Graham, Macon, and Watauga (Figure 5.1). We evaluated their exposure to certain hazards; specifically floods, wildfires, and landslides; and compared their social vulnerability and resilience from previously mentioned indicators and other sources of data. In addition, we examined the regional Hazard Mitigation Plans which included each county to evaluate how they differed in terms of recognizing and addressing climate risks and/or the discussion of resilience.

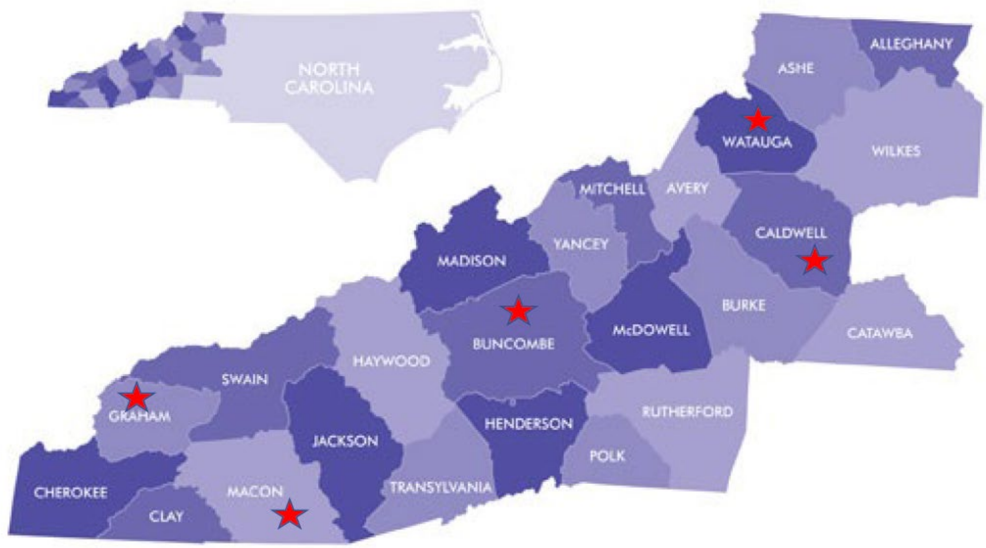


***Figure 5.1**: Counties used in Case Study (Edited image from WNC Magazine, 2020)*

While we understand that a host of other hazards have to potential to occur, flood, wildfires, and landslides were selected to focus on because of the connections to the Argonne data and Objective 1 in our research project, previous research by Maggie Sugg concerning wildfire vulnerability, and the availability of more thorough landslide data from the North Carolina Department of Environmental Quality (DEQ) for three of the selected counties.

The ultimate purpose for this case study is not to provide specific resilience planning to these counties or compare current efforts to integrate climate resilience into existing hazard mitigation plans, but rather to demonstrate how these indicators of social vulnerability and climate resilience might be useful in prioritizing issues among different county participants of regional hazard mitigation plans. This would enable a more productive process of integrating climate resilience into these plans, and assist with mapping needs to available resources among different areas based on differences in socioeconomic and resilience factors.

5.2 Climate Risk - Hazard Occurrences in the Selected Counties

To determine climate risk based on historic hazard occurrence, we used available data from regional hazard mitigation plans, and supplementing with more detailed information concerning flooding exposure from NCEI (Section 3.3) and North Carolina Department of Environmental Quality concerning landslide occurrence, to assess the level of exposure of the five counties to these three hazards (Table 5.1). With regards to flooding, each county recognizes that flooding has a high probability of occurring, even with undocumented flooding events such as Graham County. The costs in damages are striking different in each of the counties ranging from $0 in Graham County to $2.9 million in Buncombe; much of this is due to the increased built environment in more urban areas such as the cities of Asheville and Boone.

Wildfires are a moderate to high risk for exposure in each of these counties. The size and frequency of annual wildfires is strikingly different across these counties. While rural areas, such as Graham county, have few wildfires annually, these burn four to five times as much as areas than in more populated areas. As an example, Caldwell has the most documented number of fires per year, but these amount to the smallest total area burned each year of all five counties.

Landslides have some skewed elements due to the long historic nature of the underlying data from table 5.1. A substantial portion (~80 %) of landslides for Watauga county occurred as a result of a single storm in 1940. Surprisingly, in the regional hazard mitigation plan for Watauga, landslides are only a moderate risk. A reasoning for this is the different topographies of other counties in this hazard mitigation plan. Even with the exclusion of the rare storm event, Watauga falls behind only Buncombe county in number of landslides in this case study.

Table 5.1:

Summary of hazard exposure for the case study counties for flooding, wildfires and landslides. Data for this table were obtained from regional hazard mitigation plans for wildfires, the NCEI storm events database for flooding events (section 3.3), or landslide data provided by the North Carolina Department of Environmental Quality (NCDEQ). .

County	Buncombe	Caldwell	Graham	Macon	Watauga
Flooding events 2010-2019	24	35	0	9	72
Total costs of flooding 2010-2019	2902000	901000	0	5000	8710000
Hazard risk of flooding in regional HMP	High	High	High	High	High
Average number of wildfires per year	54 (2003-2012)	94	16 (2002-2016)	37 (2004-2013)	18 (2002-2016)
Average number of acres burned per year	171	123	689	165	159
Hazard risk of wildfire in regional HMP	Moderate	Moderate	High	Moderate	High
Number of landslides	372	20	1	193	2,259*
Hazard risk of landslides in regional HMP	High	Low	High	High	Moderate

5.3 Social Vulnerability in Selected Counties

Table 5.2 provides a comparison of social vulnerability between the five selected counties using the CDC's SVI, the SoVI®, and the SDoH index for each county. Color coding has been added to highlight the ranking of the counties from least vulnerable (green) to most vulnerable based on the indicators, and where available the domains (themes) used to aggregate the indicators. Multiple years are shown for the SVI to allow for relatively consistent comparisons for the SoVI (2010-2014) and the SDoH (2018).

The table demonstrates the variability in social vulnerability among the different socio-economic dimensions. While we ranked the counties on each dimension from least to most vulnerable using a color coding, note that there may not be significant differences in some cases between the actual scores. However, this provides an example of how counties could be compared for purposes of understanding differences in social vulnerability that could impact climate resilience planning. For example, the CDC's SVI score is quite different between Caldwell County and its neighbor, Watauga County. While these 2 counties are not in the same regional Hazard Mitigation Planning zone, there are many similarities between them in terms of physical hazard exposure and current overall (low) resilience scores. However, building resilience in Caldwell County could prove more difficult due to more limited economic resources and, potentially, a lower awareness of the need to do so.

Table 5.2*:*
Comparison of Social Vulnerability Measures Among Selected Counties

Legend	Least				Most
Vulnerable					
	Buncombe	Caldwell	Graham	Macon	Watauga
CDC's SVI -2014	0.22	0.40	0.30	0.26	0.09
2018	0.16	0.39	0.45	0.09	0.21
Socioeconomic theme 2014	0.04	0.84	0.64	0.30	0.50
2018	0.03	0.65	0.73	0.19	0.59
Housing composition and disability theme 2014	0.05	0.35	0.06	0.41	0
2018	0.03	0.39	0.59	0.36	0
Minority status and language theme 2014	0.38	0.12	0.09	0.13	0.09
2018	0.44	0.27	0.08	0.30	0.03
Housing and transportation theme 2014	0.78	0.13	0.23	0.24	0.39
2018	0.73	0.21	0.25	0.06	0.57
SoVI ® 2014	0.45	0.03	2.11	4.15	-0.65

5.4 Resilience Indicators for Selected Counties

Table 5.3 provides a comparison of resilience based on the two indicators (BRIC and CRSI) and the associated domains used to calculate the indicator. The table is color-coded from least resilient (red) to most resilient (green). Since the CRSI also has a risk component this is color-coded from least risky (green) to most risky (red). The scores among the counties in many cases are similar among the BRIC scores for all domains and overall scores. Counties were most different in the infrastructure domain, and most similar in the environmental domain. This highlights the difficulties in characterizing the small-scale nuances in quantifying community resilience building across geographically linked landscapes; the BRIC is more useful for state, regional, and national comparisons of community level resilience.

The CRSI scores reveal a more distinct separation of five selected counties. Some of this is due to the weighting approach that the CRSI uses as well as the inclusion of a comprehensive evaluation of natural hazard risk. Watauga is the least resilient overall community, and the nature of the calculation makes it difficult to discern what domains of resilience lead to such a stark contrast of overall CRSI score compared to other counties in this case study. Since the CRSI a) weights the overall score by governance and b) normalizes scores based on the United States median values for the governance, society, built environment, and natural environment domains, it seems like that this score is a reflected of both a low relative score nationally in governance and one or more other domains. Macon county has the highest overall resilience and the highest score in the society domain. Caldwell has the highest governance domain score, Buncombe the highest built environment domain score, and Graham the highest natural environment domain score.

Table 5.3.

Comparison of resilience based on the two indicators (BRIC and CRSI)

Legend	Least				Most
Resilient					
Risk					
	Buncombe	Caldwell	Graham	Macon	Watauga
BRIC 2015	2.77	2.71	2.62	2.52	2.73
Social	0.69	0.65	0.65	0.62	0.69
Economic	0.47	0.46	0.41	0.40	0.40
Infrastructure	0.28	0.25	0.19	0.21	0.29
Community capital	0.36	0.38	0.35	0.34	0.38
Institutions	0.40	0.41	0.46	0.39	0.38
Environment	0.56	0.56	0.56	0.57	0.59

CRSI 2017	0.96	0.84	1.18	2.07	0.20
Risk	0.51	0.28	0.18	0.31	0.17
Governance	0.25	0.38	0.24	0.23	0.26
Built environment	0.50	0.36	0.33	0.41	0.39
Natural environment	0.33	0.41	0.51	0.47	0.35
Society	0.55	0.47	0.43	0.59	0.45

5.5 Inferences from vulnerability and resilience indicators case study

One of the challenges in the evaluating constructs such as resilience and vulnerability through composite indicators is the difficulty in providing context for use at the local, community level. We present a way to utilize this information from three indicators: CDC's SVI, the BRIC, and the CRSI. We evaluate each of these for Macon and Caldwell counties because of their similarities as mostly rural counties with one city under 20,000 residents. Demonstrating how to make inferences concerning vulnerability and resilience can help guide decision-making concerning what are the current strengths of a community based on national level indicators, what weaknesses need to be addressed, what actions might be most suitable or advantageous to explore, and what additional fine-scale, bottom up data needs exists for accurate understanding of a community's vulnerability and resilience.

With respect to social vulnerability, the CDC's SVI (2018) scores demonstrate a number of differences for Caldwell and Macon counties. Caldwell County showed a moderate level of social vulnerability overall (.39) while the overall SVI for Macon County was low (.09). Examining levels of vulnerability within the aggregated SVI "themes" demonstrates unique differences. Both counties ranked relatively low in terms of risk related to housing and transportation (Caldwell, .21; Macon, .06). However, Caldwell County ranked higher in the themes of socioeconomics (.65) and housing composition and disability (.39). The Minority status and language vulnerability ranked in the median area (.27). Macon County scores for socioeconomic concerns were low (.19), moderate for housing composition and disability (.36) and moderately high for minority status and language risks (.30). From this data, it is suggested that Caldwell county climate change initiatives could focus on developing living wage jobs and stabilizing housing and services to individuals with disabilities. Macon County, conversely might be more effective in focusing on designing communications in multiple languages and developing ties with minority populations.

Resilience rankings, based on the BRIC associated domains social; economic; infrastructure; community capital; institutions; and environment. A similar comparison of these rankings for Caldwell and Macon counties provides more guidance for specific areas of intervention and planning. Caldwell County ranks most resilient in areas of economic (.46); community capital (.38), and institutions (.41) but lower in areas of social (.65); infrastructure (.25); and environment (0.56). Macon County ranks high in resilience in environment (.57), yet least resilient in areas of social (.62); economic (.40); infrastructure (.21); community capital (.34); and institutions (.39). The low BRIC score in the community capital domain can be seen to confirm the high vulnerability of the SVI theme minority status and language risks. Community capital is certainly linked with an individual's capacity to access community resources. Thus, minority populations and those with language challenges would have less resilience in terms of accessing programs that might increase their resilience to climate change or natural disaster.

Similarly, the CRSI indicates resilience in the domains of risk, governance, built environment, natural environment, and society. The CRSI also has a risk component that can be used as a comparison indicator. Comparison of Caldwell and Macon counties reveals that Caldwell County has a lower level of overall resilience (.84) while Macon County has a significantly higher level of overall resilience (2.07). Specifically, Caldwell county rankings are relatively low for domains of risk (.28), and governance (.38) but high risk in domains of built environment (.36), natural environment (.41), and society (.47). CRSI rankings for Macon County reveal that the county has lower scores for the domains of risk (.31), governance (.23), and built environment (.41), with higher scores in natural environment (.47), and society (.59). The domains of the CRSI may indicate that residents are not engaged in community governance but more engaged in the community as a whole and in the natural assets of the county.

This comparison of vulnerability and resilience demonstrates the critical need for understanding each community from a granular level as well as from an overall perspective. Each community has significantly different levels of vulnerability and resilience in differing areas. Climate change measures will need to be such that exposure to hazards is acknowledged and mitigated, vulnerabilities, both physical and social, are reduced, and resilience is increased. By understanding the components that are included in the domains of the different indexes, planners can gain an initial appreciation of the unique factors impacting each county. This comparison also serves to encourage the inclusion of a broad spectrum of stakeholders in climate change initiatives. From this comparison it is clear that the voices of minority populations should be included in the early stages of planning rather than merely invited to approve of final plans.

SECTION 6: SUMMARY AND CONCLUSIONS

6.1 Summary of Key Findings for Objective 1

Objective 1: Incorporate climate change data to produce comprehensive estimates of climate risk for hazard mitigation planning in rural western North Carolina

Objective 1 focused on using the ANL data to make inferences concerning the geographic distribution of flooding heights. With the inclusion of additional data such as monthly trends in precipitation, impervious surfaces, and documented flooding events, we were able to generate an estimate of baseline exposure of a watershed to floods (Figure 3.3). Since risk is a product of exposure and vulnerability, understanding the spatial distribution of potential flooding exposure allows decision-makers to prioritize mitigation efforts in watersheds to focus on watersheds that are highly exposed to flooding. This also helps city and county managers evaluate land-use policies to limit flooding damages.

Our findings suggest that high inland simulated flooding heights do not necessarily correlate with greater frequency of flooding events, but this could be a result of several reasons: 1) reported flood events are not necessarily in the same places with high inland flooding heights, 2) subjectivity in the community-level reporting systems for flood events could reduce the reliability of flood events reported, both in terms of quantity and characterization, and 3) high inland flooding heights might occur in low risk areas, e.g. rural areas with less potential for property damages. Other key findings support the literature concerning impervious surface's role in increasing flooding exposure, and the importance of summer thunderstorms in contributing to documented flooding events.

The uncertainty of direct climate impacts from rare events made it difficult to attempt to project increases or decreases in flooding exposure using coarse data such as monthly precipitation trends. We therefore used the available data concerning climate change from WorldClim to assess how trends in precipitation might change in the future, rather than projecting the ZIP regression model into the future. Three distinct regimes exist in North Carolina, mimicking generally the traditional three regions of North Carolina. Watersheds will, on average, see an increase of 39% in the monthly coefficient of variation, and in some months (May and October) may see an average increase of over 30% in monthly precipitation (Figure 3.4). Other notable increases are in June (22%) and July (26%), which might suggest that summertime thunderstorms could be either more frequent or more intense, or there could be more frequent days with precipitation in the early summer.

6.2 Summary of Key Findings for Objective 2

Objective 2: Identify socioeconomic disparities and associated climate vulnerability and resilience capacity in rural regions to inform policy and decision-making for underserved rural areas.

In our initial analysis regarding differential socioeconomic vulnerability across WNC, we find that the differences between WNC, particularly rural WNC, and the rest of the state are highly dependent on the way we assess vulnerability and resilience, but some common themes do exist. Regarding resilience, rural WNC has less governance and institutional (and infrastructure) capacity than the rest of the state. This means that rural WNC has, in general, less coverage for natural disasters, fewer mitigation policies in place, and less capacity in municipal expenditures for fire, police, and emergency management services. Some of this has to do with the exposure to natural hazards; rural WNC has less frequent exposure due to location, climate, and topography, but also limited experience with natural hazards when they do occur. We also have unique natural hazards, like landslides. At the same time, rural WNC demonstrates higher resilience scores in the social domain in one resilience indicator, despite lower scores from another indicator in the economic domain.

We have also discovered there is diversity in frameworks evaluating climate resilience, and also discrepancies between similar resilience indices and the scores reported. As an example, we explored two resilience indicators developed around the same time period: the Natural Hazard Screening Index (CRSI) and the baseline resilience indicators for communities (BRIC). Even when putting them on common ground (one included natural hazards in the calculation and one did not), these scores had weak correlations at best. In other words, while resilience indices can help identify geographic regions of interest, the analysis of resilience capacity must be explored at the community level.

It's important to note, however, that the use of these scores helps to identify clusters of areas with higher and lower scores across the different domains of resilience. But for purposes of integrating climate resilience planning at the community level, there may be a need for a "bottom-up" approach to building resilience capacity. The results of the case study of 5 selected counties in WNC demonstrated that variances in different dimensions of social vulnerability and hazard exposure can influence resilience planning measures at the community level; this suggests that the "one size fits all" approach in regional hazard mitigation planning might overlook specific needs at the community level.

6.3 Implications of Key Findings

6.3.1 Implications for Hazard Mitigation Planning

The primary means of addressing climate resilience capacity in rural communities has been through evaluation of hazard exposure to the area, and mitigation planning that predominantly uses historical data to determine reactive measures for disaster response. The notion of proactive steps to build resilience is often hindered by the lack of awareness and/or information, as well as economic means. Providing more forward-looking information as well as education about potential costs of unmitigated climate vulnerability is needed to help integrate steps for building climate resilience capacity into hazard mitigation plans (HMPs). This also requires, however, an understanding of how socioeconomic variability among the county participants in regional HMPs can influence steps that are taken at the community level. Aided by the use of climate data, social vulnerability metrics, and climate resilience indicators that have been evaluated in this study, communities can better estimate impending hazard events and identify specific weaknesses in climate resilience at the local level, so that HMPs can be more effective in planning for the allocation of resources for specific community needs.

Poor rural communities, such as those in Appalachia, and poor communities of color often lack a voice in regulation setting and planning and have been marginalized within climate change initiatives. It is critical then, that the goals for climate change responses promote democracy and inclusiveness. It is critical that community members be seen as equal partners in planning; requiring sensitivity to the values and concerns of the community and in particular those most vulnerable. Building resilience in populations that experience multiple vulnerabilities, as well as historical disenfranchisement, will require a clear understanding of how individuals' social networks affect their perceived ability to adapt to changing environmental conditions. In Appalachia, individuals' dependencies on social networks influences their perceived resilience to changing climatic conditions. While stable communities afford residents the opportunity to establish social relationships, the instability associated with multiple disadvantages discourages such relationships[84]. Building and enhancing resilience in these communities will require decision makers to focus on policy solutions that emphasize social networks and adaptive capacities. Increasing the resilience of minority and/or marginalized community citizens will require more culturally appropriate and context-relevant approaches in order to understand vulnerabilities of these communities. There must be explicit inclusion of marginalized community members in climate change outreach, and planning efforts in order to ensure climate readiness for all residents.

6.3.2 Implications for Communications Infrastructure in Rural Areas

A primary topic in the discussion of rural resilience (climate and other stressors) is on the adequacy of the communications structure in these regions, particularly as it relates to capacity of disaster response and emergency management. Indeed, this is relevant to the discussion on building climate resilience capacity because so many residents of residential areas tend to lack access to broadband or other communication service providers, either due to geographic location and/or economic capacity. A survey in Watauga County provides some insight into the issues with resilience in a rural communications infrastructure[85]. The map in Figure 6.1 shows the responses from unserved or underserved participants from the survey, demonstrating that most of the county has survey participants who have inadequate access to service. This includes those with no internet access at all (25% of respondents), no cellular internet access (74% of respondents), no cable internet access (78% of respondents), no satellite internet access available (74%), and no DSL internet access available (75%),

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[84] Gilster, M.E & C.L. Meier (2017) Formal and Informal Social Organization: Do Geography, Structural Inequality, and Other Forms of Social Organization Matter? Journal of Community Practice, 25:2, 172-189
[85] Broadband Survey, High Country Council of Governments for Watauga County, May 2017.

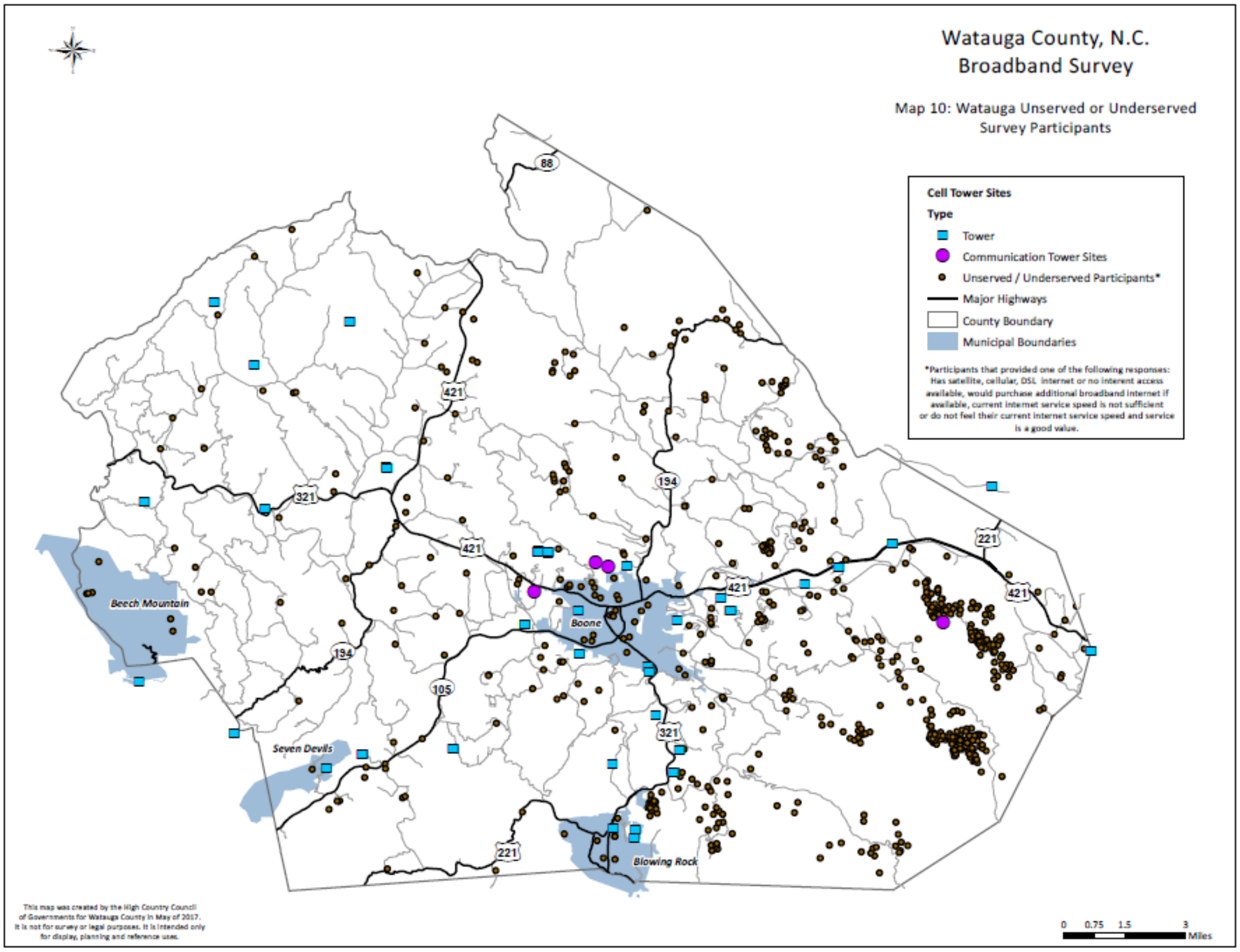

Figure 6.1 - *Unserved or Underserved Broadband Survey Participants in Watauga County, NC*

Interestingly, from feedback in this survey, economic capacity did not seem to be the reason for lack of access, as indicated by the high percentage (91%) of respondents who said they would be willing to purchase broadband, if available. Consequently, this is important to the climate resilience capacity-building discussion in that it is an issue with physical access, rather than economic barriers, that highlight the need for expanding and improving the communications infrastructure in rural regions. The data from this survey helped to identify deficiencies in access to sufficient communication and, if combined with mapping of high-risk hazard exposure areas as well as high social vulnerability scores (like examined in this study), the results would be useful for identifying and prioritizing areas to expand communications infrastructure, particularly broadband.

6.3.3 Implications for Natural Resource and Land Use Management

In preparation of the 2020 North Carolina Climate Risk Assessment and Resilience Report, the Working Lands Stakeholder Group was formed to help evaluate different ways that agricultural and forest land could be used to assist with building climate resilience. It is widely thought that forest management practices are a primary "natural climate solution" because of the significant untapped potential to reduce carbon density, prevent soil erosion, protect watersheds, and reduce wildfire if forests were more properly managed and cleared land was reforested. [86] Researchers at Duke University have produced resources that demonstrate the opportunities for forest management practices that can produce community resilience benefit across North Carolina (Figure 6.3). In WNC, the primary areas of benefit include protection in urban areas (flooding) and in water supply watersheds. Thus, it is clear that the vast amount of forested property in WNC, while being the target of climate risk (wildfires and landslides), is also the primary asset for building climate resilience. By using the data from this study on hazard vulnerability as well as resilience capacity, we could map the areas of greatest need to those with greatest protection opportunities.

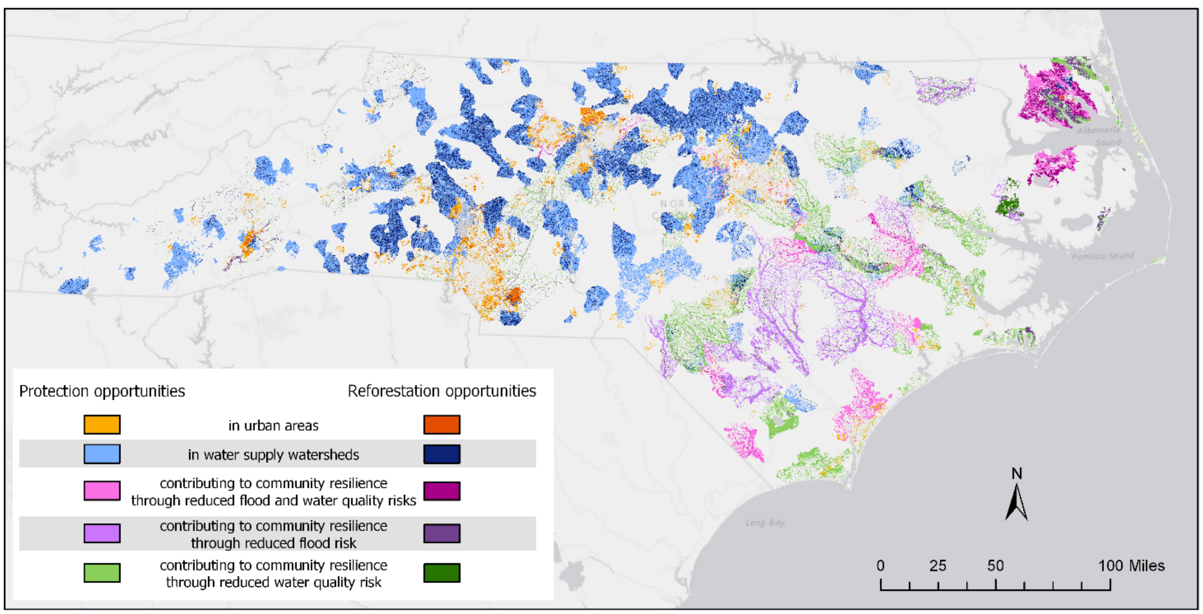

***Figure 6.3**: Protection and reforestation opportunities with community resilience benefit (Source: Nicholas Institute for Environmental Policy Solutions at Duke University)*

[86] *Natural climate solutions for the United States*, Fargione, J.E. et al, Science Advances, Nov 2018:(4) 11

6.4 Concluding Remarks

In this study, we focused on the need to integrate the concept of social justice into the discussion of climate resilience in rural communities. Climate change and social vulnerability are deeply interconnected[87] and are problems rooted in the structures, systems, and values of local societies and economics. Historically, the disenfranchisement of the most vulnerable communities from climate change decision making have included broad consequences, such as the reduction of community cohesion, feelings of powerlessness, and socioeconomic damage. Sensitivity to local values and concerns of the community will make it clear that climate change acts as a threat multiplier, exacerbating poverty, environmental degradation, and social instability. Responding to climate change and reducing social vulnerability requires an intersectional and transformational approach that includes the voices of those most at risk.

Place-conscious approaches acknowledge that the resources needed to revitalize communities are unequally distributed across regions[88]. It is important to consider that place-based and place-conscious approaches not only promote change within a geographic area, but they may also diffuse to other communities. At the same time, the influence of adjacent communities also suggests that climate change initiatives should create collaborations across community lines. What happens in one community is related to what is happening in surrounding communities. Exploring the spatial autocorrelation among resilience and vulnerability attributes (Section 4.5.3) helps us understand the spatial dependence (or independence) of resilience and vulnerability, and identify areas for collaborations based on those spatial patterns.

A number of authors have pointed out that outcomes to problem-solving improved when stakeholder input was obtained early and repeatedly throughout the planning process[89] [90]. As this report has demonstrated, vulnerability, exposure, and resilience must be assessed in terms of the actual experience of the people living and working within each community. In addition, the need for input from the business community in rural areas is essential, as community resilience is vital to the sustainability of economic development and job growth.

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[87] Boetto, H. , A Transformative Eco-Social Model: Challenging Modernist Assumptions in Social Work, *The British Journal of Social Work*, Volume 47, Issue 1, January 2017, Pages 48–67

[88] Turner, M.A. (2017). Beyond People Versus Place: A Place-Conscious Framework for Investing in Housing and Neighborhoods. Housing Policy Debate, Volume 27, Issue 2.306-314

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APPENDIX

***Table A.1**.*

Western North Carolina (WNC) counties and their 2013 population, their rural urban classification, and specifics concerning flooding events during the period of 2010 to 2019.

County	Population [20]	Rural-Urban Continuum Code [20]	Total flooding events [21]	Total costs (Thousands $) [22]
Alexander	37198	(2) Metro - Counties in metro areas of 250,000 to 1 million population	6	11
Alleghany	11155	(9) Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area	14	510
Ashe	27281	(7) Nonmetro - Urban population of 2,500 to 19,999, not adjacent to a metro area	34	311
Avery	17797	(8) Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area	16	230
Buncombe	238318	(2) Metro - Counties in metro areas of 250,000 to 1 million population	24	2902
Burke	90912	(2) Metro - Counties in metro areas of 250,000 to 1 million population	36	282
Caldwell	83029	(2) Metro - Counties in metro areas of 250,000 to 1 million population	35	901
Cherokee	27444	(9) Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area	3	13
Clay	10587	(9) Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area	1	0
Cleveland	98078	(4) Nonmetro - Urban population of 20,000 or more, adjacent to a metro area	3	20
Graham	8861	(9) Nonmetro - Completely rural or less than 2,500 urban population, not adjacent to a metro area	0	0
Haywood	59036	(2) Metro - Counties in metro areas of 250,000 to 1 million population	4	22
Henderson	106740	(2) Metro - Counties in metro areas of 250,000 to 1 million population	46	243
Jackson	40271	(6) Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area	5	53
Macon	44996	(6) Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area	9	5
Madison	33922	(7) Nonmetro - Urban population of 2,500 to 19,999, not adjacent to a metro area	6	2552
McDowell	24505	(6) Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area	24	864
Mitchell	15579	(7) Nonmetro - Urban population of 2,500 to 19,999, not adjacent to a metro area	9	616
Polk	20510	(8) Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area	11	439
Rutherford	67810	(4) Nonmetro - Urban population of 20,000 or more, adjacent to a metro area	10	46
Surry	73673	(4) Nonmetro - Urban population of 20,000 or more, adjacent to a metro area	24	1024
Swain	13981	(8) Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area	11	3622
Transylvania	33090	(6) Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area	47	239
Watauga	51079	(5) Nonmetro - Urban population of 20,000 or more, not adjacent to a metro area	72	8710

Wilkes	69340	(6) Nonmetro - Urban population of 2,500 to 19,999, adjacent to a metro area	30	35
Yadkin	38406	(2) Metro - Counties in metro areas of 250,000 to 1 million population	9	503
Yancey	17818	(8) Nonmetro - Completely rural or less than 2,500 urban population, adjacent to a metro area	9	208

Table A.2. Description of All Data and Data Sources for the Creation of the SDoH Metric

Table 1. SDOH Variables		
Description of Variable	Variable Name	Source
% Total Population: Male: Under 5 Years	MPopUnder5	2018 American Community Survey, 5-Year Estimate
% Total Population: Male: Under 18 Years (Population 5-9, 10-14, 15-17)	MPopUnd18	
% Total Population: Male: Over 65 Years (Population 65-74, 75-84, 85 and Over)	MPop65Over	
% Total Population: Female: Under 5 Years	FPopUnder5	
% Total Population: Female: Under 18 Years (Population 5-9, 10-14, 15-17)	FPopUnd18	
% Total Population: Female: Over 65 Years (Population 65-74, 75-84, 85 and Over)	FPop65Over	
% Total Population: Under 5 Years	TPopUnder5	
% Total Population: Under 18 Years (Population 5-9, 10-14, 15-17)	TPopUnd18	
% Total Population: Over 65 Years (Population 65-74, 75-84, 85 and Over)	TPop65Over	
Median Age:	MedAge	
% Total Population: White Alone	PopWhite	
% Total Population: Black or African American Alone	PopBlack	
% Total Population: American Indian and Alaska Native Alone	PopAmInd	
% Total Population: Asian Alone	PopAsian	
% Total Population: Native Hawaiian and Other Pacific Islander Alone	PopHawaii	
% Total Population: Some Other Race Alone	PopOthRace	
% Total Population: Two or More Races	PopTwoRace	
% Households: Family Households: Other Family: Female Householder, No Husband Present	FHH_NoHusb	
% Renter-Occupied Housing Units ((Total Renter Housing / Total Housing) * 100)	RentHouse	
% Occupied Housing Units: with Related Children of the Householder Under 18	OcH_Rchild	
% Renter-Occupied Housing Units: with Related Children of the Householder Under 18	ReH_Rchild	
Average Household Size	AvgHHSize	
Average Household Size for Renter-Occupied Housing Units	AvgRHHSize	
% Population 25 Years and Over: Less than High School	Pop_LessHS	
% Population 25 Years and Over: High School Graduate or More (Includes Equivalency)	Pop_HSGrad	
% Population 25 Years and Over: Some College or More and Bachelor's Degree or More	Pop_ColBac	
% Population 25 Years and Over: Master's Degree or More and Professional School Degree or More and Doctorate Degree or More	Pop_HighEd	
% Population 16 Years and Over: in Labor Force	Pop_LabFor	
% Population 16 Years and Over: in Labor Force: in Armed Forces	Pop_ArmFor	
% Population 16 Years and Over: in Labor Force: Civilian	Pop_Civil	
% Population 16 Years and Over: in Labor Force: Civilian: Employed	PopCvEmp	
% Population 16 Years and Over: in Labor Force: Civilian: Unemployed	PopCvUnem	
% Population 16 Years and Over: Not in Labor Force	PopNoLabFo	
% Civilian Population in Labor Force 16 Years and Over: Employed	CvPopEmp	
% Civilian Population in Labor Force 16 Years and Over: Unemployed	CvPopUnem	
% Housing Units: Mobile Home	HousMobHom	
% Occupied Housing Units: Mobile Home	OHMobHom	
Median Gross Rent as a Percentage of Household Income in the Past 12 Months (Dollars)	MGR_HHInc	
% Families: Income Below Poverty Level	FIn_Bpov	
% Workers 16 and Over: Drove Alone and Carpooled	WrkDA_Cp	
% Workers 16 and Over: Public Transportation (includes Taxicab)	WrkPT	
% Workers 16 and Over: Bicycle and Walked	WrkB_W	
% Total: No Health Insurance Coverage	NoHlthCov	
% Households with Housing Costs more than 30% of Income	HHcost_30I	
% Own Children under 18 Years: Children Living with Single Parents	ChU18LivSP	
Percent Below Poverty Level - Population for whom poverty status is determined	PerPopBPov	
Percent of Households with No Available Vehicle	PHH_NoVeh	

Percent of Households with 1 Vehicle Available	PHH_OneVeh	
Count of Childcare Centers normalized by the Total Population	Childcare	HIFLD
Count of Banks normalized by the Total Population	Banks	
Count of Fire Stations normalized by the Total Population	FireStat	
Count of Mobile Homes normalized by the Total Population	MobHome	
Count of Public Health Departments normalized by the Total Population	PubHlthDep	
Count of Urgent Care normalized by the Total Population	UrgentCare	
Count of Churches/Areas of Worship normalized by the Total Population	Worship	
Count of Colleges normalized by the Total Population	College	NCCGIA NC OneMap
Count of Emergency Shelters normalized by the Total Population	EmergShelt	
Count of Gas Stations normalized by the Total Population	GasStation	
Count of Hospitals normalized by the Total Population	Hospitals	
Count of Nursing Home normalized by the Total Population	NursHome	
Count of Public Libraries normalized by the Total Population	Libraries	
Count of Pharmacies normalized by the Total Population	Pharmacies	
Count of Private Schools normalized by the Total Population	PrivSchool	
Count of Public Schools normalized by the Total Population	PubSchool	
HPSA Data - Count of Mental Health Facilities per Census Tract	MH_Count	HRSA
HPSA Data - Count of Primary Care Facilities per Census Tract	PC_Count	
Total Population (B03002) Hispanic or Latino Origin by Race	TPop_Hisp	2018 American Community Survey, 5-Year Estimate
Not Hispanic or Latino: White Alone	White_NHsp	
Not Hispanic or Latino: Black or African American Alone	Black_NHsp	
Total Population (B19001B) Household Income in the Past 12 Months (in 2018 Inflation-Adjusted Dollars) (Black or African American Alone Householder)	TP_BHHInc	
Less than $10,000	BHH_L10	
$10,000 to $14,999	BHH_149	
$15,000 to $19,999	BHH_199	
$20,000 to $24,999	BHH_249	
Combined income values of less than $25,000 for Black or African American Householder	BHH_Less25	
Total Population (B19001H) Household Income in the Past 12 Months (in 2018 Inflation-Adjusted Dollars) (White, Not Hispanic or Latino Householder)	TP_WHHInc	
$100,000 to $124,999	WHH_1249	
$125,000 to $149,999	WHH_1499	
$150,000 to $199,999	WHH_1999	
$200,000 or More	WHH_200Up	
Combined income values of greater than $100,000 for White, Not Hispanic/Latino Householder	WHH_Grt100	
Total Population (B19001) Household Income in the Past 12 Months (in 2018 Inflation - Adjusted Dollars)	TPop_HHInc	
Less than $10,00	HH_L10	
$10,000 to $14,999	HH_149	
$15,000 to $19,999	HH_199	
$20,000 to $24,999	HH_249	
Combined income value of less than $25,000	HH_Less25	
$100,000 to $124,999	HH_1249	
$125,000 to $149,999	HH_1499	
$150,000 to $199,999	HH_1999	
$200,000 or More	HH_200Up	
Combined income value of greater than $100,000	HH_Grt100	