WATKINS, JAMIE ARIAIL. M.S. Pluvial flooding and flood rescues in Rowan County, NC: An analysis of 9-1-1 call data for years 2011 - 2021. (2024)
Directed by Dr Sarah Praskievicz. 72 pp.

Flooding is the most widespread and costly natural disaster worldwide. The effects of climate change and development are expected to significantly increase losses of life and property due to flooding over the next century. While coastal and riverine flooding are well understood and their attendant flood risk zones mapped, flash flooding events in urban areas are not as well understood or mapped. In the years 2018 and 2020, Rowan County Emergency Services responded to record numbers of flood rescue calls due to pluvial flooding. This paper examines 9-1-1 call data in Rowan County from 2011 through 2021. Patterns in call frequency, spatial distribution, meteorological conditions, and changes in land use patterns were analyzed to better understand the evolving nature of flood rescue calls in Rowan County in hopes of building community resilience and sustainability.

A combination of record rainfall events and clearing of land for development were found to have contributed to the increase in call volume for flood rescues. The spatial distribution of calls was found to be much more dispersed in the later portion of the study period than observed in the earlier portion of the study. Additionally, the length of time from the when the first call was received to when the last call came in was longer in the later portions of the study. Greater rainfall increased impervious surface, and decreased evapotranspiration capacity may have contributed to flooding events that stretched over two and three days in the later portions of the study period.

PLUVIAL FLOODING AND FLOOD RESCUES IN ROWAN COUNTY, NC:

AN ANALYSIS OF 9-1-1 CALL DATA

FOR YEARS 2011-2021

by

Jamie Ariail Watkins

A Thesis
Submitted to
the Faculty of The Graduate School at
The University of North Carolina at Greensboro
in Partial Fulfillment
of the Requirements for the Degree
Master of Science

Greensboro

2024

Approved by

Dr. Sarah Praskievicz
Committee Chair

DEDICATION

To my Rowan County Fire, Rescue, and EMS family. It has been the great privilege of my life to have served alongside you. Thank you all for your wisdom, support, and camaraderie.

Special thanks to former Battalion Chief Kevin Dodd, whose words of wisdom, “Smile, wiggle your toes, and keep on walking,” have reminded me to persevere on more occasions than I can count and whose humor and friendship I will always cherish.

APPROVAL PAGE

This thesis written by Jamie Ariail Watkins has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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April 10, 2024
Date of Acceptance by Committee

March 13, 2024
Date of Final Oral Examination

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CHAPTER I: INTRODUCTION

Floods are the most destructive and frequent cause of disasters worldwide (Shah et al. 2017, Malik 2022). The effects of climate change are projected to alter rainfall patterns and produce more intense and longer-lasting cloudburst storms over the remaining course of this century (Kundzewicz et al. 2014). Between 2000 and 2014, flooding was the cause of nearly 40% of all natural disasters worldwide and was responsible for $397.3 billion in damage (Tomar et al. 2021). The cost of all flooding disasters was calculated in 2019 to be $45 billion and was projected to rise to $535 billion by 2050 (Knighton et al. 2021). As the global population becomes increasingly urbanized and developable land outside of historic floodplains becomes ever more scarce, flooding events that damage homes and businesses and cause injury or death to humans will become more common (Cashman 2009). Between 2005 and 2014, 709 deaths were attributed to flooding in the United States, and 69% were due to flash flooding (Smith et al. 2015). Inland flooding represents a significant risk to the health and safety of the people living in both urban and rural areas and is projected to increase in both severity and frequency as time passes. Flooding also represents a threat to vital assets and infrastructure such as roads, electricity, and telecommunication lines; water, sewer, and gas lines; schools, hospitals, and churches; individual homes and multifamily residential complexes; local government buildings, businesses, and more (NC DEQ 2020). A clear understanding of flooding patterns is required at the state, county, and city levels so that we may rise to meet the challenges of climate change.

Overview of Flood Types

The geography of a given area and the weather patterns experienced in the region determine the sort of flooding hazards experienced locally. Flooding can be broken down into four categories:

Coastal flooding typically happens near an ocean shoreline and is usually associated with large tropical storms. Low-lying coastal areas frequently impacted by tropical storms are vulnerable to rising ocean levels brought about by storm surges. This is further compounded as the storm moves inland, dumping water on the rivers and streams that eventually make their way to the ocean, where the mouths of said rivers are already experiencing backwater flooding from storm surges.

Fluvial or riverine flooding, happens mainly inland and occurs when rainfall exceeds the capacity of local rivers and their tributaries to carry runoff away from an area at a speed and volume greater than or equal to that produced by the rainfall event. These events tend to be contained within a floodplain and are characterized by the amount of water spilling over the river's banks. Fluvial flooding is a natural process and is necessary to maintain healthy ecosystems of rivers and their floodplains. However, urbanization and more intense rainfall events, attributed to climate change, are causing more frequent and severe fluvial flooding events (Gilbert et al. 2009, Miller and Hutchins 2017).

Pluvial or flash flooding refers to shorter-duration events that occur when a large amount of water enters an area over a relatively short time and overwhelms the local stormwater conveyance or natural soil infiltration capacity. These types of floods happen much more often in developed areas. Densely developed urban areas have much more impervious surface area, less vegetative cover, and a high concentration of people and infrastructure. The combination of lost evapotranspiration capacity and diminished rainfall infiltration creates greater runoff volume and velocity, resulting in flash floods that threaten property and human lives.

Urban flooding is usually a combination of pluvial and fluvial flooding made worse by the increased runoff created by urban sprawl. Urban floods can cause significant injuries, deaths, and property damage due to the high numbers of people affected in a relatively small area (Gilbert et al. 2009). Urbanization and the attendant increase in the impervious surface area impact watersheds in urban areas by concentrating and accelerating polluted runoff, altering the natural flow of receiving waters, and increasing the temperature of receiving waters by absorbing and transporting heat from pavement, sidewalks, and other hard surfaces in the built environment (Miller and Hutchins 2017). Here, the focus is on pluvial urban floods.

Flood Factors

Climate change and human development contribute to mean annual streamflow changes throughout the United States. Wang and Hejazi (2011) set out to tease apart the relative contributions of climate change and direct human actions in altering mean annual streamflow. Their study found that climate change contributed slightly more to streamflow changes than human actions like development. However, the team concluded that if more watersheds were analyzed, the impacts of development could very likely be found to be much stronger than their study showed. That increased impervious surface area increases runoff is widely accepted. However, quantifying how much extra runoff is produced per unit of impervious surface area is difficult to calculate precisely. By examining the land use changes and weather conditions experienced by three highly urbanized areas over a span of seven years, Liu, Li, and Wang (2021) found that impervious surfaces explained roughly a quarter of all increased runoff observed over the study period. Additionally, they observed that as little as a 20% increase in impervious surface area of smaller sub-basins was associated with a transition from minimal to significant alterations in runoff patterns.

Pluvial flooding occurs when the amount of rainfall in an area exceeds the infiltration capacity of the soil and the ability of natural and human-constructed conveyance systems to move the water downstream at a rate greater than or equal to the speed at which the rainfall is accumulating (Glago 2020). Urban drainage systems are very sensitive to variations in the distribution of rainfall across the system. The duration of the storm has as significant an impact on flooding as does the total amount of rainfall. Longer-duration storms typically have multiple peaks throughout the storm event, while shorter-duration storms typically have only one peak (Tang and Trefzger, 2023). Pluvial flooding in urban landscapes is becoming more frequent and therefore an increasing number of people and homes are affected. This increase also leads to increased costs associated with injuries, deaths, property damage, and disruption of local economies (Falconer et al. 2009). Unfortunately, pluvial flooding is not included in the National Flood Insurance Program, making exact figures quantifying losses from such events hard to find.

Nevertheless, a growing body of research shows the increasing detrimental socio-economic effects of pluvial flooding in the United States (Falconer et al. 2009). Urbanized landscapes in North Carolina produce 75% more peak streamflow during a rainfall event than comparable fully forested areas. The difference was most pronounced during the growing season, indicating that reduced evapotranspiration in urban areas significantly contributes to increased pluvial or flash flooding in developed landscapes (Boggs and Sun 2011). Climate change is projected to impact evapotranspiration and contribute to the destabilization of the hydrological cycle. Higher temperatures and increased levels of carbon dioxide cause plants to constrict their stoma which reduces the amount of water vapor they release into the air (Kim, Band, and Ficklin 2017).

Most stormwater sewer systems are designed to convey the runoff volume associated with a “design storm.” A “design storm” is usually a weather event with either a two-year or a ten-year return interval. The higher the return interval, the more intense the associated storm event. Each "design storm" has an associated volume of rainfall, and storm sewer systems are sized to handle that amount of runoff (Rosenzweig et al. 2019). Pluvial flooding can occur even when stormwater drainage systems are appropriately sized for the "design storm." Rainfall events associated with pluvial flooding often dump a large volume of rain over a small area in a very short period of time. This intensity limits infiltration into the local soils and reduces uptake by trees and other plants (Palla et al. 2018).

Nature-based or "green" stormwater drainage systems can be used to augment "grey" or human-constructed stormwater conveyance to produce better water quality, mitigate excess runoff, and combat air pollution and the urban heat island effect. Individual installations of structures like green roofs and rain barrels can help decrease the total annual runoff of a given highly localized area, but there are few studies exploring the widespread deployment of green infrastructure as a means to control pluvial flooding (Kabisch et al. 2017). Cost-benefit analysis of traditional stormwater improvements shows that basin-wide measures are required to produce ecologically and financially meaningful reductions in pollution (Kalman et al. 2000). The sporadic nature of green infrastructure implementation further limits the ability to study its viability as an option to mitigate flooding. Still, the demonstrated benefits show that green stormwater drainage systems are worth considering as a way to augment existing grey infrastructure and, in some cases, as a more cost-effective alternative to traditional box drains and pipes (Kabisch et al. 2017).

Adding to the difficulties in sizing stormwater collection systems to reduce pluvial flooding is something called "hidden urbanization." Hidden urbanization is a widespread phenomenon in which the amount of impervious surface area calculated from official site plans is less than what is observed on the ground or measured by orthographic imagery. Simply put, property owners make changes (driveway expansion, patio installation) that increase impervious surface (Stronbach et al. 2019). While no single one of these changes alters the hydrology of an area in an appreciable way, the cumulative effect is enough to overwhelm the runoff collection system that was designed and built to service that area (Tang and Trefzger 2023).

Risk Management

Identifying high-risk flood-prone areas and developing a response plan in advance of flooding events can significantly reduce the risk of loss of life and or property due to urban flooding (Yalcin 2020). Mapping flood risk using Geographic Information Systems (GIS) is increasingly important as the spatial analysis capabilities of the technology provide the tools to gain a clear understanding of not only the location of flooding events, but also the terrestrial conditions that affect the distribution and severity of flooding events (Eleutério, Martinez, and Rozan 2010). Projecting future flooding events is heavily dependent upon historical records. This presents a challenge as climate change continues to produce storms that break from the "norms" established by historical records. Compounding this challenge is the ever-increasing amount of impervious surface due to land use changes and urban development (Kim, Lee, and Sung 2016). In short, much of our pre-planning efforts will need to rely increasingly on computer modeling and forecasting as the century progresses so that we can formulate the most effective strategies for flood risk mitigation.

Watershed modeling using raster and vector data in desktop GIS applications is useful when analyzing flood risk. While more sophisticated and expensive methods are available, simple modeling methods have been shown to provide excellent overviews of regional basins while remaining cost-effective (Balstrom and Crawford 2018). In a study comparing various machine learning models, Chen, Huang, and Chen (2021) found that decision tree-based models were the most efficient calculators of flood risk and that, in particular, the Gradient Boosting Decision Tree (GBDT) method gave the most reliable results. The absence of data on the location and capacity of human-built stormwater conveyance structures can hamper accurate simulations of flooding events. The inclusion of such data causes pronounced differences in floodwater depth and extent when compared to the results of the same scenario being run without said data (Hossain Anni, Cohen, and Praskievicz 2020).

Researchers have widely accepted that completely eliminating flood risk is impossible and that efforts should be focused on effective risk management and resilience strategies (Kubal et al. 2009). However, what constitutes "effective" risk management programs is often hard to quantify and subjective. A more appropriate rating system is to determine whether a course of action has a positive, negative, or negligible effect on the people it is meant to help (Kruczkiewicz et al. 2023). Resilience, sustainability, and vulnerability are all interconnected ideas, and many times, sustainability and resilience are used interchangeably. This is not entirely accurate. Sustainability deals with common conditions and events. It can be thought of as the everyday maintenance of a status quo that could endure for the foreseeable future. Resilience, on the other hand, deals with short-term, low-probability but high-impact events. Resilience focuses on creating the innate ability to quickly recover from an event, in this case, flooding, that could otherwise have devastating effects. Communities cannot consider themselves truly sustainable if they are not resilient. Diversification is considered a key indicator of resilience. Vulnerability is the likelihood of a person, place, or community suffering significant negative impacts from flooding (Li et al. 2019). The warning time of fluvial, or riverine, flood risk is inversely related to the damage done by the flood. Shorter warning times, lower knowledge of precautionary measures, and a perception of minimal personal risk is associated with greater injuries and losses

(Kienzler et al. 2015). Pluvial flooding warning times are unlikely to increase over the coming decades, so a focus on education and pre-planning is key to any urban area's resilience strategy (Netzel et al. 2021). The National Institute of Building Sciences found that for every dollar spent retrofitting and upgrading buildings to match the current flood code, three to eleven dollars of property damage could be avoided (Multi-Hazard Mitigation Council 2019).

The United Nations' Sendai Framework for Disaster Risk Reduction 2015–2030 calls for a shift away from disaster response towards a focus on prevention and mitigation. The framework advocates for an integrated approach to flood mitigation that involves structural and non-structural measures and creating a more people-centered approach to flood risk management. Within the realm of non-structural measures, a growing emphasis is being placed on bottom-up, context-specific approaches and an exploration of community-based data sources such as citizen science, participatory mapping, and community-based monitoring (Ortiz et al. 2024). Using community-based data sources, like geo-referenced social media posts, allows us to map flooding issues in real-time at or near the exact spot where the problem occurs. Stream gauges only provide information about water levels at a static location, and if flooding exceeds the height of what the gauge can measure, the data from it are of very little use. Remote sensing and satellite imagery data can be verified, but finding data at the required spatial and temporal resolution can be difficult. Community-sourced data are not always verifiable, but this method provides much finer-resolution data quickly, which can help emergency management personnel when responding to pluvial flood events (Li et al. 2017). User-generated data can also reveal gaps in current flood risk mapping practices.

Emergency Planning

In order to adequately pre-plan for flood events, all scenarios must be evaluated to formulate multiple contingency plans. Flooding rescues are complicated by the fact that the rising waters present an obstacle to getting equipment and personnel to the scene in a timely fashion (Chang, Tseng, and Chen 2007). Emergency planning and response require coordination between departments and organizations at the local, regional, state, and federal levels (WHO 2017). Emergency Management can be used as both a means of preventing disasters, and as a way of responding to disasters across different scales as the event unfolds (Huang, Wang, and Liu 2021).

Population growth and changing weather patterns are creating a greater need for water rescue services from flooding events. Effective water rescue management involves pre-planning and training. By analyzing call logs and weather data from past events, emergency management can begin to predict future call conditions and locations. This information is a vital part of building a sustainable and resilient community (Helmke et al. 2010).

In North Carolina, Iredell Rowan Regional Hazard Mitigation Planning Team ranked their concerns about all hazards facing the region. Committee members were each given the same amount of “play money” to “spend” mitigating one or more hazards (AECOM 2019). Floods were the top-scoring concern, garnering 33% of all monies “spent” on hazard mitigation by the committee (Table 1).

Table 1 - Results of "Mayor for a Day" Table Top Exercise

Hazard Type	Percent of "Money Spent" on Hazard Mitigation
Flood	33.33%
Winter Weather	19.61%
Drought/Extreme Hea	11.76%
Hazardous Materials	9.80%
Torado	9.15%
Hurricane	6.54%
Wildfire	5.88%
Thunderstorm/Lightning/Hail	3.92%

Incident reports and other data points generated by flood victims can be used to enhance the validity of flooding predictions. By incorporating these datasets into maps that include hydrology and impervious surfaces, Emergency Management personnel can create more accurate plans to respond to pluvial flooding (Gaitan, van de Giesen, and ten Veldhuis 2016).

Public Education and Risk Perception

A public that is well educated about the hazards facing their particular community and has an accurate understanding of the risks to their personal safety are more likely to adopt best practices and are less likely to do things that turn them from a citizen into a victim (Glago 2020). Most hurricane-related deaths and injuries occur inland when people try to drive through flooded roads (WRAL Staff 2008). At least 10 of the 46 people whose deaths were blamed on Hurricane Florence in North Carolina drowned when their vehicles were swept away in floodwaters. It is unknown how many of those resulted from people driving around barriers or on roadways where warning signs had been removed. In one high-profile case, a one-year-old boy drowned in Union County after his mother drove past barricades and into floodwaters (Stradling 2019). The Fire Life and Safety Educator's (FLSE) role is to change the general public's behaviors through outreach programs and educational messaging. An educated public makes better decisions, resulting in fewer injuries, disabilities, and deaths from fire and other potential hazards (Geisler

2018). Effective education programs are shown to increase the accuracy of people's response to a fire and thus guide them to avoid becoming victims in the first place. While many educational programs focus on school-aged children, messages targeting adults aged 18 to 80 also increase that group's overall knowledge and response accuracy. Middle-aged adults were shown to be the most likely to react correctly to an encountered hazard, which suggests special attention should be paid to improving lessons targeted to younger adults and senior citizens (Huseyin and Satyen 2020).

Education is not the only factor that affects how people respond when faced with an emergency. Personal risk perception, knowledge, and housing conditions all influence how members of the public react to flooding conditions. These factors should be taken into account when designing FLSE programs (Netzel et al. 2021). To properly address the community's educational needs, FLSE personnel should have an in-depth understanding of the different cultural, racial, and socio-economic challenges faced by their community at large and by individual neighborhoods within their service area. By tailoring messaging to reach people where they are, FLSE personnel can better empower their community members to make the best decisions to protect themselves and their property (Jennings, 2023). Having the trust of the community one serves is one keystone of being part of the emergency services profession. Risk information is more likely to be accepted and translated into appropriate behavior changes if it is conveyed by a trusted source. A source of information is more likely to be trusted when the person relaying the message has several things in common with their target audience. Additionally, whether the risk communicator is a government official, a volunteer rescuer, or a neighbor affects risk perception and adoption of appropriate behaviors. When risk communicators are volunteer rescuers, audiences are more likely to trust them and translate their message into appropriate flood risk reduction efforts (Seebauer and Babcicky 2018).

People who live with a disability experience problems with one or more of the following: vision, hearing, mobility, learning, memory, cognition, communication, mental health, and social relationships (CDC 2020). People who have special needs often lack the resources to effectively get themselves out of harm's way during a flooding incident. During Hurricanes Katrina and Rita, many people in the flood zone were prevented from accessing the resources they needed due to their disabilities. Some were unable to leave their homes. Some could not be reached by rescuers. Several of those who did manage to escape were turned away from shelters that were not prepared to meet the needs of the disabled community (Gilbert et al. 2009). Even low-magnitude flooding can seriously increase emergency response times, which can lead to negative outcomes for patients (Yu et al., 2020).

Low-income and non-White people are more likely to live in flood-prone areas that are becoming increasingly uninhabitable. Federal, state, and local programs that provide assistance commonly disproportionately help more affluent White populations. County and municipal governments are better suited to study and understand the needs of their communities. Conducting studies to identify the most vulnerable neighborhoods or sections of neighborhoods and distributing relief funds accordingly is a more equitable way to address the issues facing people living in the flood zone (Kruczkiewicz et al., 2023). Flooding from Hurricanes Matthew (2016) and Florence (2018) wreaked havoc on the ecology of North and South Carolina. Raw sewage from wastewater treatment facilities, overflowing sanitary sewers, and hog lagoons combined with polluted runoff from washed-out coal ash ponds. In-situ monitoring devices went offline and the availability of data on the exact scope of environmental impact is less than robust.

To add insult to injury, the majority of the impacts were to the coastal plains of both states, which are home to many of the most impoverished counties in the region (Schaffer-Smith et al. 2020).

Flood patterns in urban areas are changing due to a combination of climate change and increased impervious surface area and the frequency of flooding events is expected to grow over the next several decades (Kundzewicz et al. 2014). Studies have also found a link between reduced evapotranspiration in urban areas and an increase in pluvial or flash flooding in developed landscapes (Boggs and Sun 2011). Flooding presents a significant source of risk for loss of life and property in North Carolina and is expected to become a more frequent and severe problem as the state's population grows and as the effects of climate change intensify (NC DEQ 2020). Many of the most devastating floods in North Carolina have been associated with tropical cyclones. These large systems form far away and are tracked for days or weeks before making landfall, which gives a greater lead time for preparation measures. Warning times for pluvial flooding are much shorter. Recently, the United States Geological Survey (USGS) teamed up with the City of Charlotte and Mecklenburg County, North Carolina, to create a flood information and notification system (FINS) to address the need for prompt notification of flood conditions (Konrad, n.d.).

Mapping flood risk from fluvial flooding is a well-established discipline, as evidenced by the National Flood Insurance Program administered by FEMA. Pluvial flooding, however, is not always accurately captured by FEMA's flood risk maps. For example, when analyzing 3-1-1 calls related to flooding from Hurricane Harvey, a team of researchers found that over half of the calls were associated with parcels located in the FEMA "X Zone." The X Zone is considered to be very low risk for flooding, but the 3-1-1 call data suggest otherwise (Rainey et al. 2021).

Pluvial flooding, due to its swift onset and brief nature of duration, is harder to predict and map through traditional means (Gaitan, van de Giesen, and ten Veldhuis 2016). Modern problems call for modern solutions; one such solution is using emergency call data to map pluvial flood risk.

Oliva and Olcina (2023) argue for using 1-1-2 (the emergency response telephone number in Spain) call data to map flood extent and study specific events' spatial and temporal nature. Their research determined that using emergency call data is an effective if under-utilized methodology for studying pluvial flooding. Emergency call data give us a clear picture of what is happening on the ground during a flood. Calls are spawned in real-time at the location of events as they unfold. In the case of calls related to flooding, the reported issues revolve around the disruption of everyday life and economic activities. Callers can provide detailed information to emergency dispatchers that other sources of data would not capture. Cell phone use has increased significantly over the past decade, making it easier than ever for people witnessing or experiencing an emergency to call emergency services like 9-1-1 (McFadden 2018). Similarly, non-emergency calls are on the rise due to the ubiquity of smartphones and can also generate data that can be used to study flooding. 3-1-1 call data was used to examine the extent of flooding caused by Hurricane Harvey in Galveston, Texas, in what FEMA had designated as the "low-risk zone" (Rainey et. al. 2021). This study will use methods similar to those of Oliva and Olcina (2023) and Rainey et al. (2021) in that 9-1-1 call data will be used to map and study pluvial flooding events.

Research Questions

Question 1. What are the observed trends in water rescue events in Rowan County for years 2011-2021?

Hypothesis 1. I expect to find an increase in call volume for individual events as well as more frequent events in the latter years of the study period.

Question 2. What are the controls on the spatial patterns of water rescues in Rowan County for years 2011-2021?

Hypothesis 2. I expect to find a pattern of increased call volume over a wider area of the county. I expect to find a pattern of land use change that contributes to the increased call volume and more widely distributed call locations.

Question 3. What meteorological conditions are associated with water rescue events in Rowan County for years 2011-2021?

Hypothesis 3. I expect to find an increase in rainfall before and during an event which is associated with an uptick in calls related to pluvial flooding.

Question 4. What socio-economic conditions may be influencing the most heavily impacted areas within the study?

Hypothesis 4. I expect to find that census block groups with higher than average indicators of susceptibility to environmental injustice also experience a high concentration of flood calls throughout the study period.

CHAPTER II: METHODS

Description of Study Area

Rowan County, North Carolina, is located in the Piedmont region of North Carolina, northeast of Charlotte (Figures 1 & 2). Interstate 85 connects the county to the Charlotte Mecklenburg Metro Area and the Piedmont Triad Metro Region and transports an average of 105,000 people through the county daily (NC DOT, n.d.). At 511 square miles, or 1325 square kilometers, the county is home to more than 149,000 people and is the 19th largest county by population in the state (U.S. Census Bureau 2023). The birthplace of Food Lion grocery, Cheerwine soda, and Stanback headache powders, Rowan County hosts more than half a million visitors yearly (Rowan County Government Staff 2020). Notable geographic features include the Yadkin River, which serves as the county's northeastern border, High Rock Lake, Dunn's Mountain, Tucker Town Reservoir, and Dan Nicolas Park (Martin 2011). The past decade has seen dramatic increases in economic growth and development within the county. In 2019, the Rowan County Economic Development Commission (EDC) managed over 90 projects that created 1,284 new jobs and amounted to more than $114 million in investments. Over the past decade, the EDC has worked with local governments and private partners to make more than 2,000 acres of land "shovel ready" for industrial development (Rowan County Government Staff 2020).

Figure 1 - Map of Location of Rowan County, NC

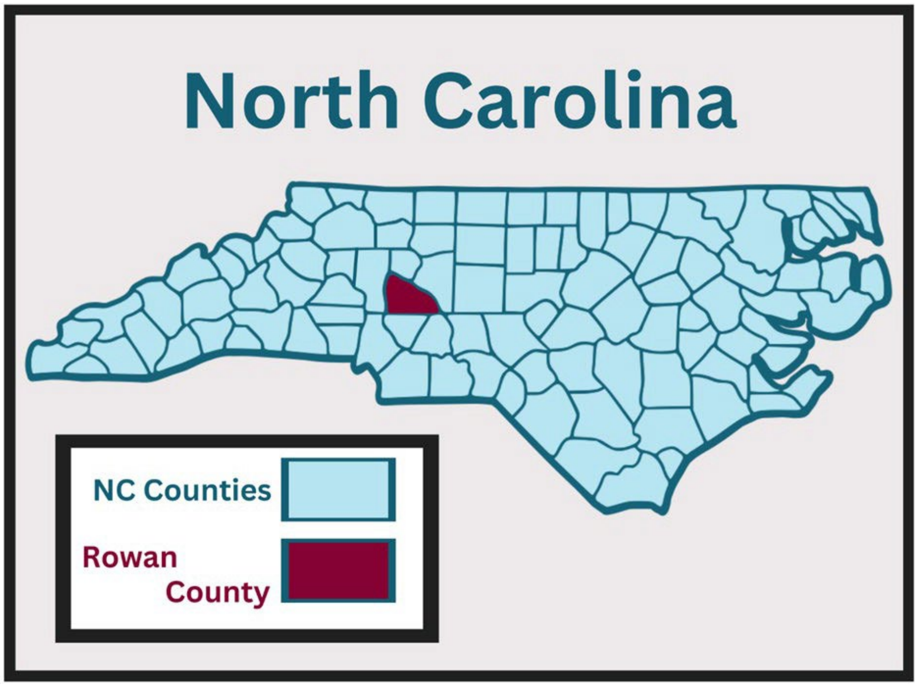
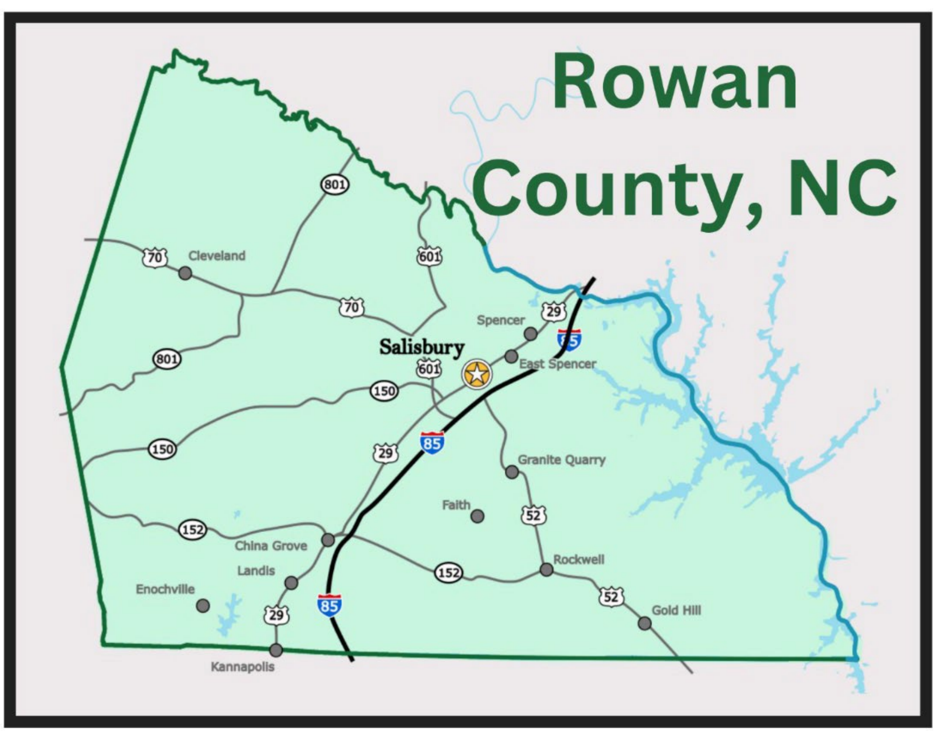


Figure 2 - Map of Rowan County, NC



Call Data Collection

Since 2008, Rowan County Emergency Services 9-1-1 Call Center has been certified as an Emergency Medical Dispatch center. The Emergency Medical Dispatch system is a nationally accredited and standardized methodology by which calls for emergency services are answered, classified, coded, and dispatched. All calls received are filtered through a decision tree by the dispatcher based upon the information provided by the person calling for help. The dispatcher asks a series of standard questions. The caller's answers are recorded in the system which then determines the number and type of resources to send to the scene of the incident. The Computer Aided Dispatch system selects individual units based on their type, service district, availability, and proximity to the call. The dispatcher then sets the tones off for each responding unit or station, followed by a radio message that provides the location of the call, the type of emergency, the number of patients involved, and any other relevant information. Records of each call are kept in a database and can be requested via the Rowan County website as they are public information. To retrieve call data relevant to my study, I submitted a "Confidential Tape / Records Request Form" online via the Rowan County website for all 9-1-1 dispatched calls ("CAD data") coded "Water Rescue" from 1 January 2011 to 31 December 2021 (Rowan County Government Staff, n.d.). I received a spreadsheet of 1,087 individual call records, which I sorted chronologically. I then broke the records into smaller spreadsheets by year. A single incident can generate several dispatched calls due to the involvement of multiple agencies. I eliminated duplicate entries and extraneous data to create a spreadsheet of unique events for each year in the study. Each call's location and notes were used to determine whether or not the event was truly related to urban flooding. Most of the calls in the years 2011 – 2017 took place on High Rock Lake or the Yadkin River and were clearly due to recreational boating incidents. Several calls stood out as they were not associated with the lake or the river and were color-coded for further investigation. At this point, I realized that there was no data for 2014, and the data request had not captured a call in 2020 that I was personally on. My anticipation of finding that call within the data allowed me to detect a potential for other "holes" in the data. I reached out to the head of the 9-1-1 center and fellow Rowan County Rescue Squad Member Chief Phil York, and explained my concerns about potential gaps in the data I had to complete my research. We spoke at length and determined that many calls likely met my research criteria but were not captured in the initial records request due to how the calls were initially coded through the emergency dispatch system. Chief York determined that the best way to capture more relevant calls would be through a keyword search through call notes. In the world of emergency dispatch this is termed a "wildcard search." Chief York ran two "wildcard" searches for the keywords "flood" and "floodwater" in the notes of all dispatched calls in the study period. The "wildcard searches" yielded two PDFs with a combined 807 records. Many of these calls were due to someone reporting a flooded home caused by a plumbing issue or a safety concern regarding the activation of the caller's flood lights. These documents also had multiple entries for the same event for the same reasons as mentioned above. I did not have the option to sort these entries by date, but I was able to use the search function in Adobe to look for incidents that happened in 2014. While a few calls in 2014 mentioned flooding in the notes, none were related to either a boating incident or an urban flooding event. The wildcard search did yield a new type of call that was helpful in mapping urban flooding events, "High Water." A "High Water" call is simply a way to mark a portion of a road that needs to be barricaded because of flooding. This gave me additional information to use when the call notes of an urban flooding call were unclear on the true nature of the incident. I cross-referenced my calls that were color-coded for further investigation with the dates of calls for high water and was able to rule out a few incidents by the lack of high water calls on the dates in question.

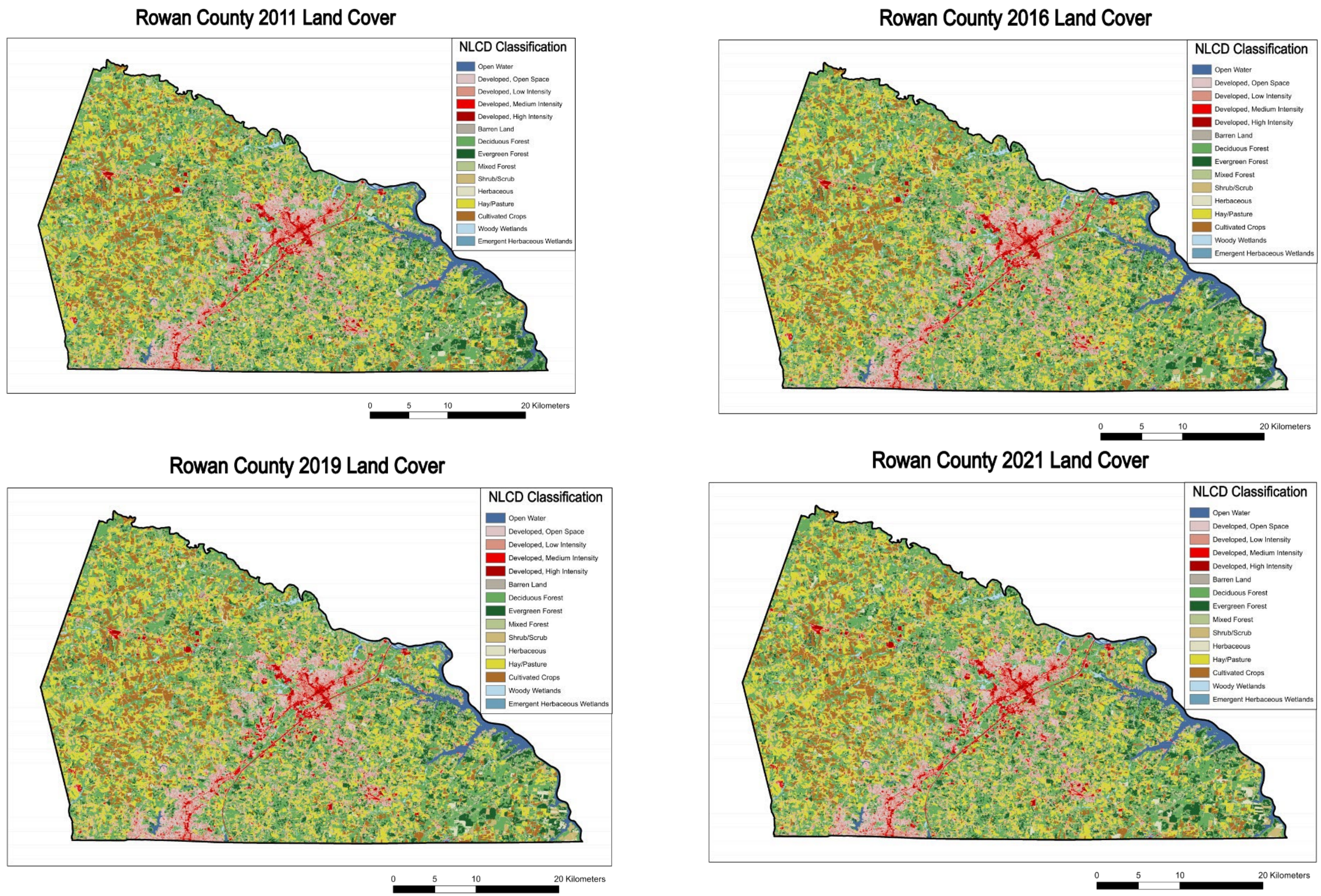
I added the new data gleaned from the wildcard search to the existing spreadsheets for each year in which I had call data. I then separated each call year spreadsheet by month. From there, the spreadsheets were further sorted into high water and rescue calls by year and month. The resultant spreadsheets contained street addresses, location names, intersections, or street blocks but provided no coordinates with which to plot the data. To geo-code each call, I used Google Maps, dropped a pin at the call's location, and copied the latitude and longitude into columns labeled "y" and "x", respectively. I then saved a copy of each spreadsheet as a comma-separated values table, imported it into ArcGIS using the "Add X Y Data" option, selected the .csv file, and set my x and y values to correspond to the eponymous dropdown selection. I made sure the Geographic Coordinate System was set to "GCS_WGS_1984" and clicked "OK." I repeated this process for each layer of rescue location and high-water calls. In all, I added 16 layers of point data that represented nine separate events in four different years: 2015, 2017, 2018, and 2020.

Land Cover Analysis

I downloaded the National Land Cover Database for years 2011, 2016, 2019, and 2021 as those most closely related to the significant years of 9-1-1 call data (U.S. Geological Survey 2023, 2021b, 2021a). The 2011 land-cover data were used as the baseline against which the other two layers would be analyzed for change. The assumption is that the land-cover characteristics captured by the 2019 data would most closely reflect those present during the 2018 flooding calls, with the same holding for the 2021 layer and the calls that took place in 2020. The calls that took place in 2015 and 2016 were both analyzed using the 2016 land-cover data as the "event year" land-cover conditions for those events.

I first created land-cover layers for Rowan County. I used the county boundary layer I had isolated from an NC DOT shapefile with all 100 North Carolina counties as a mask to extract raster data for each year of land-cover data I had downloaded. As with the buffer areas, 2011 was used as the baseline and raster counts were converted to square kilometers (Figure 3).

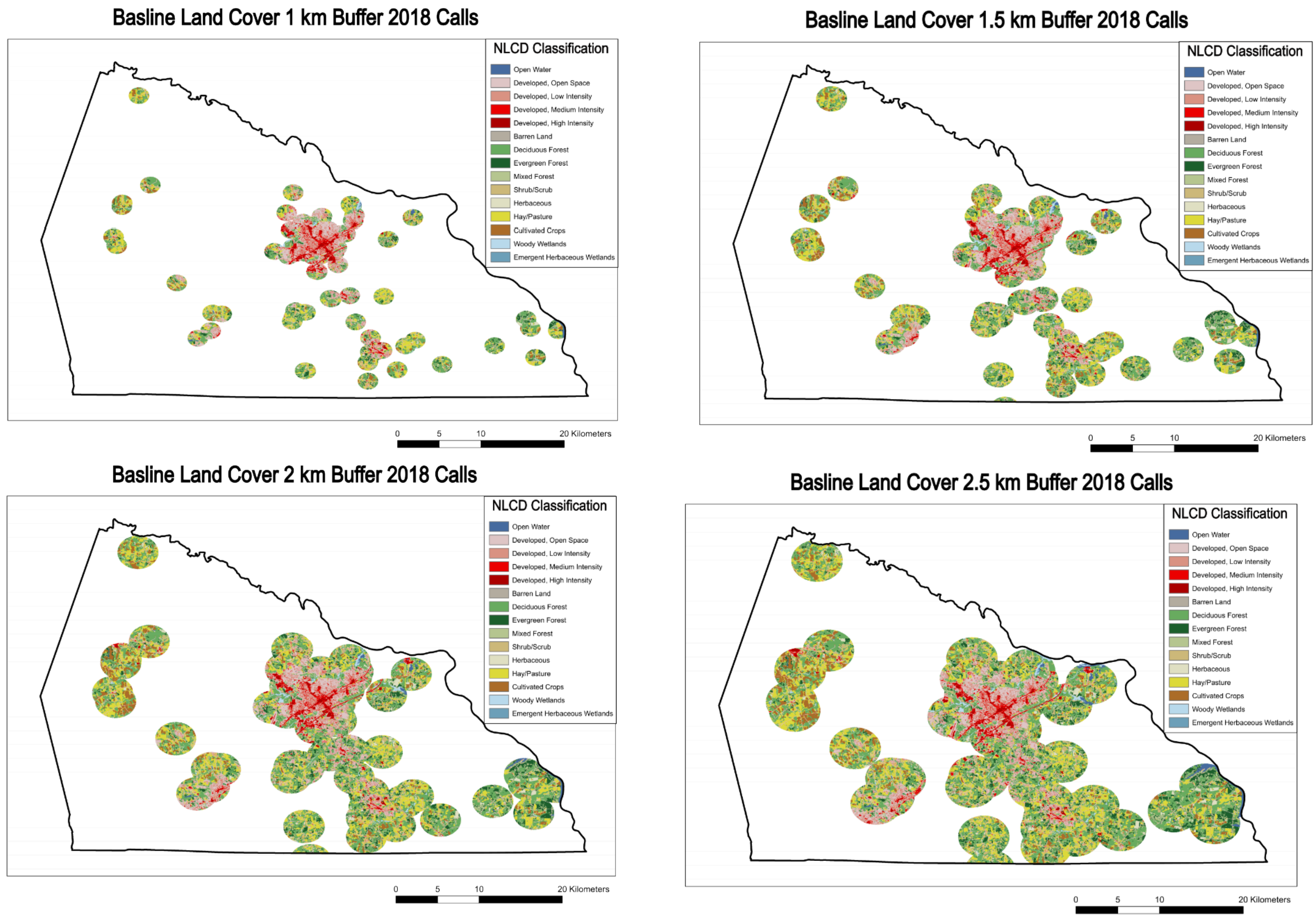
Figure 3 - NLCD Land Cover Maps



I grouped calls by year and used the buffer tool to create a 1-kilometer buffer around each call in 2015. I then used the union tool to merge all those individual circles into one shape, which was then used as a mask feature to extract the raster data from the 2011 land cover data. I then repeated this process with the 2016 land cover data. The resultant attribute tables were exported as dBASE files, opened in Excel, and then analyzed for change.

I realized that to compare the land-cover changes within the buffer zones against those across the whole of Rowan County, I needed to ensure my buffers were only capturing land cover inside the county boundaries. I exported each of the resultant layer's attribute tables into Microsoft Excel to analyze the land cover changes over the study period. I then used the county boundary layer as a mask for extracting the data from each of the iterative buffer layers for each year of call data (Figure 4).

Figure 4 - Iterative Buffer Analysis of 2018 Call Data



I first converted the raster count into square kilometers to make the resultant area more relatable. Having 30-meter by 30-meter resolution data means that each raster is 900 square meters or 0.0009 square kilometers. Converting the raster count is as simple as multiplying by 0.0009, and I created a formula to do so. I then added up all the space within each year to ensure the area matched. Once I had a total area for the 2018 1-km buffers, it was time to see what had changed. I first calculated the percentage of the total area occupied by each land cover type (km^2 of individual type/km^2 of whole area). I then calculated how many square kilometers of cover were gained or lost from 2011 to 2018 for each cover type (2018 km^2 – 2011 km^2). I took the resultant number and divided it by the baseline figure for that land-cover type to calculate the percentage change for the individual type (km^2 change/2011 km^2 of individual type). Beneath each column of km^2 change, I placed a SUM formula to ensure the number was zero. Since the total area of each year was the same, any changes would simply amount to a reconfiguration where the total should be zero. If the figure was anything else, then I knew there was a flaw in my data somewhere, and I could take steps to correct it. I repeated this process for the 2020 calls.

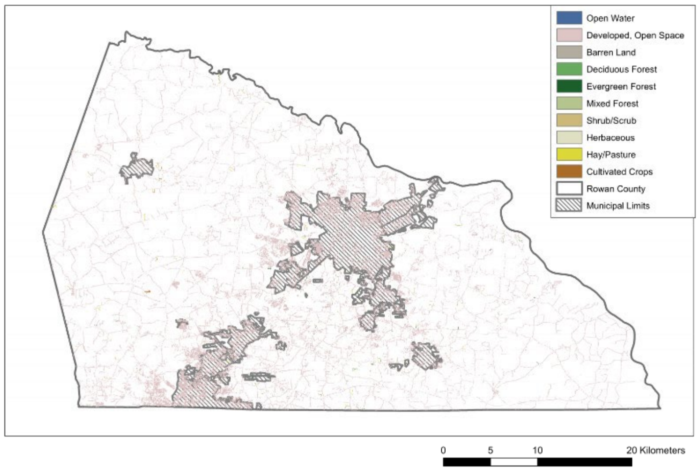
Land-cover change was initially evaluated using two different formulas. The first was to calculate the percentage of the total area of the county occupied by each land-cover type in each of the four years for which I have data. For example, in 2011, deciduous forest occupied 405.71 square kilometers or 29.90% of the total area of Rowan County. To calculate this percentage, I divided the area occupied by deciduous forest by the total land area of Rowan County: 405.71/1356.96 = 0.299. In 2019, the area occupied by deciduous forest decreased to 399.58 square kilometers or 29.45% of the entire county. I repeated this process across the buffer areas comparing the total area occupied by each event year and buffer size to the proportion of that whole occupied by each land-cover type. This yielded very small changes in the percentage of the whole across both the county and the buffer areas. I then decided to compare each land cover type to itself across the years. For example, that same 405.71 square kilometers of deciduous forest in 2011 was used to calculate the number of square kilometers lost in 2019: 399.58 - 405.71 = -6.13. I then took that -6.13 and divided it by the 405.71 square kilometers from the baseline year, which equals -0.0151 or -1.51%. I repeated this process across the tables for the county and the buffer areas.

I revisited my land-cover analysis and decided to do some reverse engineering. Rather than compare the raster counts in the exported attribute tables from one year to the next, I looked at what the lands that were developed in 2021 started out as in 2011. Using the Extract by Attributes tool, I selected all the raster values out of the 2021 land-cover data that were coded as Developed, Open Land. I then used that as a mask to extract the land-cover types from 2011. I was trying to determine out of everything that ended up being developed open land, what did it start out as? I then did the same for low, medium, and high-intensity development.

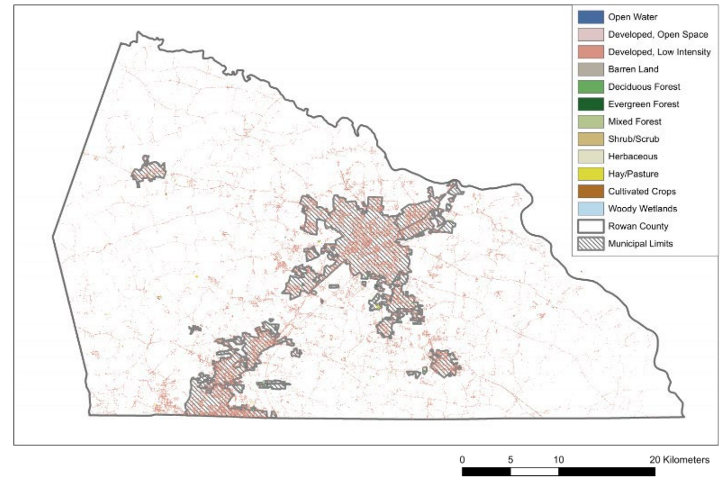
The final comparison was between the 1.5-km buffer areas of the 2018 and 2020 calls against the whole county. This time, instead of looking at individual land-cover classifications, I grouped them into two categories: Impervious Area and Undeveloped. Open, Low, Medium, and High-Intensity Development were counted as Impervious Area, and everything else was considered Undeveloped. I used Excel to calculate the percentage of area occupied by Impervious Area for the county and the buffer areas for 2018 and 2020 (Figure 5).

Figure 5 - Impervious Surface Reverse Engineering Maps

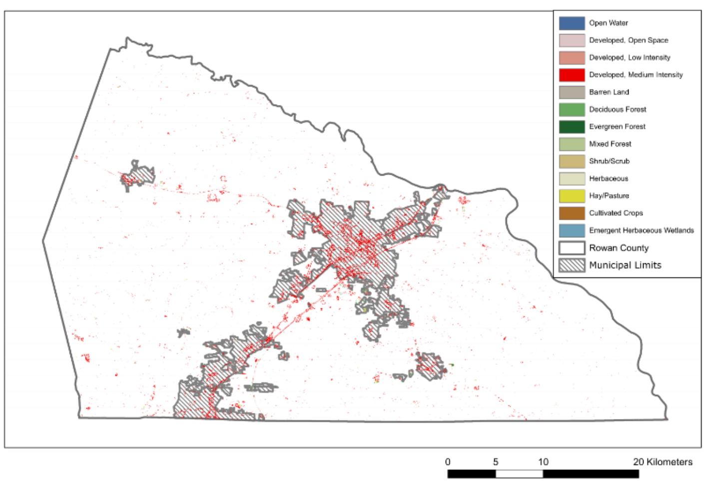
Original Land Cover Types of all Land Labeled Developed, Open Space in 2021



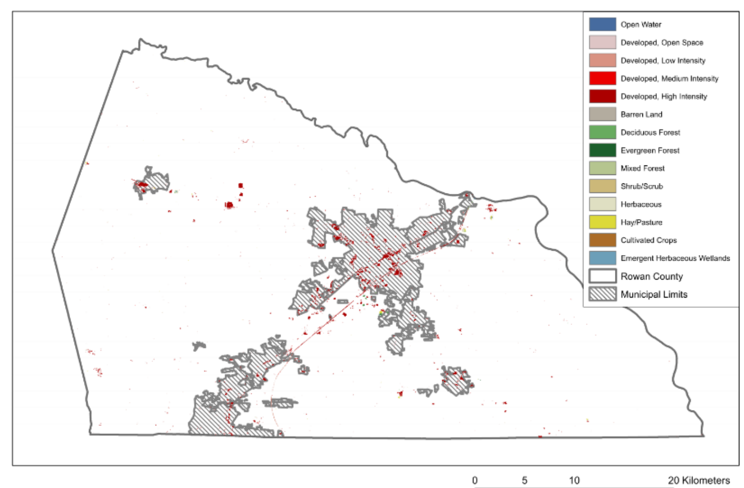
Original Land Cover Types of all Land Labeled Developed, Low Intensity in 2021



Original Land Cover Types of all Land Labeled Developed, Medium Intensity in 2021



Original Land Cover Types of all Land Labeled Developed, High Intensity in 2021

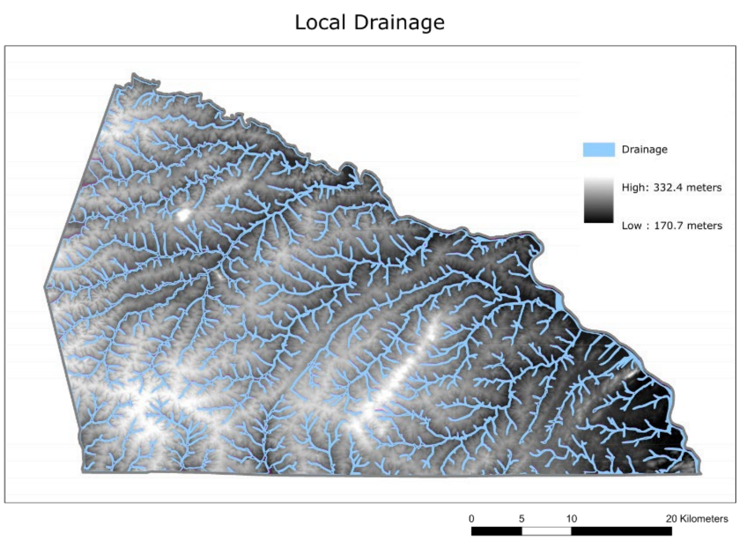


Height Above Nearest Drainage

To explore if the absolute and relative elevations of call locations changed over the study period, I downloaded a digital elevation model (DEM) from the United States Geological Survey (cite). I then added this to my map and used the "Fill" tool under "Spatial Analyst – Hydrology" to fill in any imperfections in the layer. From that filled DEM, I then used the "Flow Direction" tool to calculate the eight-way flow direction of each cell in the layer.

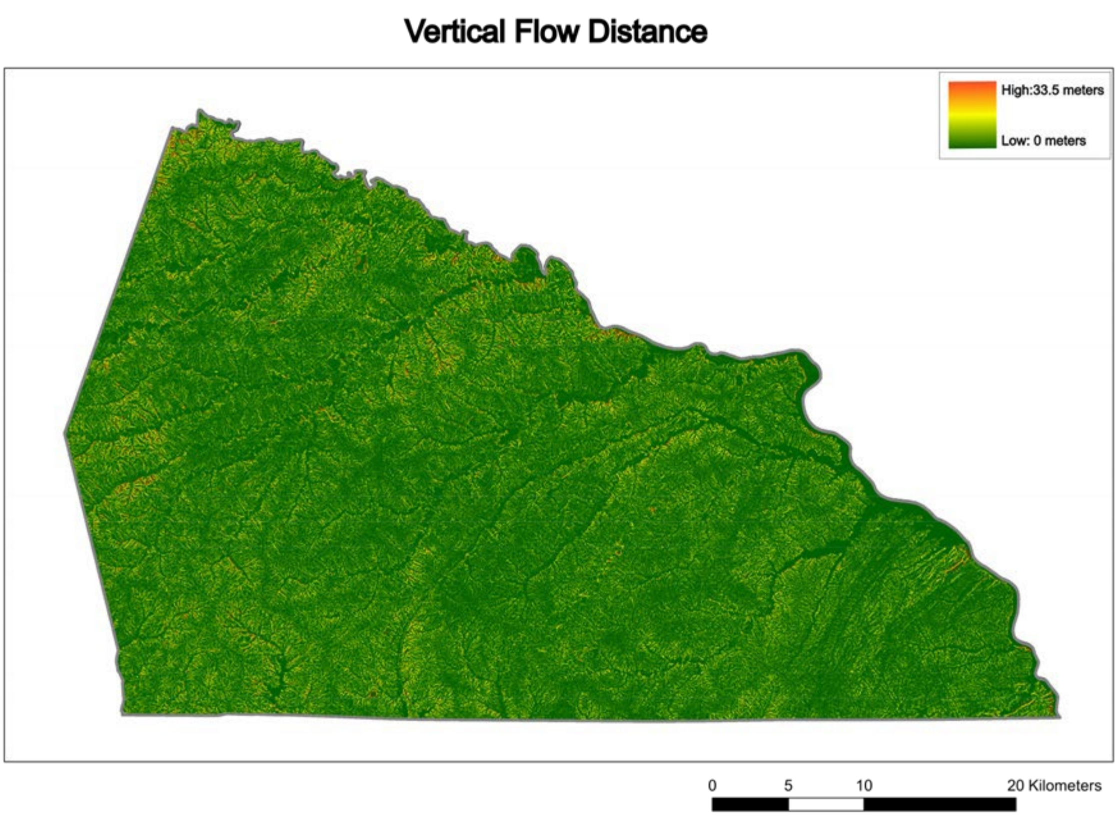
The resultant layer was then used to calculate "Flow Accumulation" for each cell. Once that layer was done, I opened the properties tab, selected "Symbology", changed it to "Classified," "Manual" classification, and set the number of classes to two. The next step was to delineate the drainage network. I did this through trial and error by experimenting with the class break values. Zero to "X" was represented with no color, as everything at or below "X" value was not a high enough accumulation to be considered a stream, and everything from "X" to the highest accumulation value was represented by a bright blue line on the map. This layer was overlaid with the filled DEM, and when the blue lines looked like they reasonably represented a stream network, the corresponding value of "X" was set at 500 (Figure 6).

Figure 6 - Local Drainage Calculated from Eight-Way Flow Direction



The last layer that I needed to create was the Height Above Nearest Drainage (HAND). To do this, I used the “Flow Distance” tool. This required me to input my drainage layer, my filled DEM, and my flow direction layers. I set “Distance Type” to measure vertical distance in meters and made sure the “Direction Type” was set to “D8” to match the flow direction layer. The resultant layer was labeled “Vertical Flow Distance” (Figure 7) and was used to calculate the height above the nearest drainage for each call location by using the “Extraction” tool, selecting “Extract Values to Points,” setting the “Input Point Features” as the plotted call data points, and the “Input Raster” as the flow distance layer. I then opened the attribute tables for each layer, exported them as dBase files, and converted them into Excel files for further analysis. I repeated this process for each layer using the filled DEM as the “Input Raster” layer to extract the absolute elevation for each call location.

Figure 7 - Map from which height above nearest drainage was extracted.



Weather Data

I downloaded weather data that corresponded to each event from NC State's repository (North Carolina State Climate Office 2021). I was able to retrieve data at one-hour resolution for the dates on which the events of interest occurred. The hourly readings were listed in order from the top of the hour prior to the first call of each event to the top of the hour after the last call for each event. For example, the August 2018 event's first call was at 18:50 on August 1, and the last call came in at 18:35 on August 3. Therefore, the precipitation dataset for that event runs from 17:00 on August 1 to 19:00 on August 3. I repeated this pattern for each of the remaining events. I then sorted each event's calls by chronological order and tallied up how many calls came in each hour and recorded that in the corresponding hourly cell. I then looked at each block of calls and recorded the highest HAND value for that hour's calls and the highest absolute elevation for each hour's calls. I repeated this process for each event and labeled the resultant spread sheets "Event Month/Year Hour by Hour Analysis." It was from these spreadsheets that I was able to graph patterns of hourly call volume, hourly rainfall, and elevation values related to call locations.

Each of these spreadsheets was then used to create a synopsis that plotted out total rainfall for each event, the average soil moisture value, the 48-hour pre-event precipitation, total calls per event, highest HAND per event, and highest absolute elevation per event.

To better understand the precipitation preceding each event, and to compare it to Intensity-Duration-Frequency (IDF) curves, I downloaded the IDF information for Salisbury from the National Oceanic and Atmospheric Administration (NOAA) as a spreadsheet (NOAA, n.d.). I had to convert the IDF precipitation values from inches to centimeters by multiplying each value by 2.54. I used data from the Cardinal Request Builder to create spreadsheets for each event that showed the total rainfall values, in centimeters, at 1-hour, 2-hour, 3-hour, 6-hour, 12-hour, 24-hour, 2-day, 3-day, 4-day, 7-day, 10-day, 20-day, 30-day, 45-day, and 60-day time stamps before the beginning of each event. For the hourly time intervals, I looked at the time stamp on the first call of each event, backed up to the first whole hour, and began reverse engineering my precipitation records from there. For example, the first call of the August 2018 event came in at 18:50 on August 1st. I took the top of the hour precipitation reading from 17:00 that day as my - hour duration event, since that would be the measurement across a whole hour prior to when calls first started coming in. For the 2-day through 60-day precipitation records, I downloaded precipitation data from the same source at the 24 hour resolution level. The first call for the August 2018 event came in on August 1, so the data for two days prior is the sum of rainfall for July 30 and 31. I compared precipitation values to the IDF table's precipitation amount to match its corresponding storm interval if the rainfall was significant enough to qualify as a 1-, 2-, 5-, 10-, 25-, 50-, 100-, 200-, 500-, or 1000-year event. From this information, I was able to determine the recurrence interval for pre-event rainfall and the precipitation that occurred during each event.

In addition to IDF data, I examined the USGS stream gauge data for the Yadkin River from station number 02116500, which is located at Yadkin College, and is the closest station to Rowan County. Using custom date ranges for each of the events in the years 2018 and 2020, I captured images of the line graph of the gauge height and noted the date and time at which the highest watermark was recorded. I then compared the timeline of each event to the corresponding hydrograph to determine if the Yadkin River's levels were unusually high during one or more of the events in the study.

Social Justice Dimensions

The EPA tracks seven socioeconomic indicators of vulnerability to environmental injustice. These indicators are related to census block groups so that the geographic distribution of these impacted communities can be easily conveyed via color-coded maps. Data are reported as percentiles of the percentage of people in the vulnerable group in the block group relative to their percentages in the entire state of North Carolina. The metrics include the percentage of people of color, low-income families, unemployed workers, people with limited English, people age 25 or older without a high school diploma, children under age five, and seniors over age 64 (U.S. EPA 2014). Of these metrics, people of color, low-income families, and people over the age of 64 are more likely to reside in flood prone areas (Schaffer-Smith et al. 2020; Kruczkiewicz et al., 2023).

People of Color: The percent of individuals in a census block group who list their racial status as other than White, or who list their ethnicity as Hispanic or Latino.

Low Income: The precent of a block group’s households where the annual income is less than or equal to twice the federal poverty level.

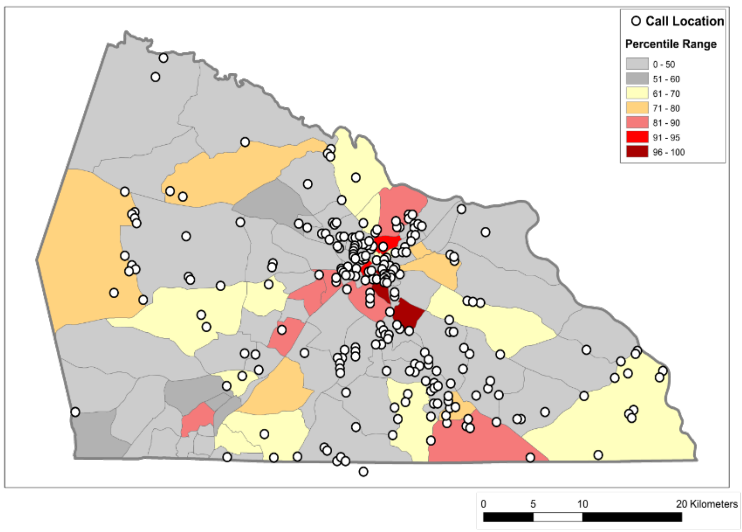
Over Age 64: The percent of people in a block group over the age of 64 years.

I obtained the information needed by launching the EJ Map Tool and typed in the zip code for Salisbury. I then selected Reports, Select County, and clicked on Explore Reports. Clicking the Get Data Table button allowed me to download all the data for Rowan County, North Carolina, in an Excel spreadsheet. I then went to the US Census Bureau and downloaded the shapefiles that contained all the census block groups for North Carolina. I opened the spreadsheet and copied all the census blocks for Rowan County, saved them to a new spreadsheet as comma-separated values, and used the joins and relates feature in ArcGIS Desktop to join them to the census block group shapefile by block group ID.

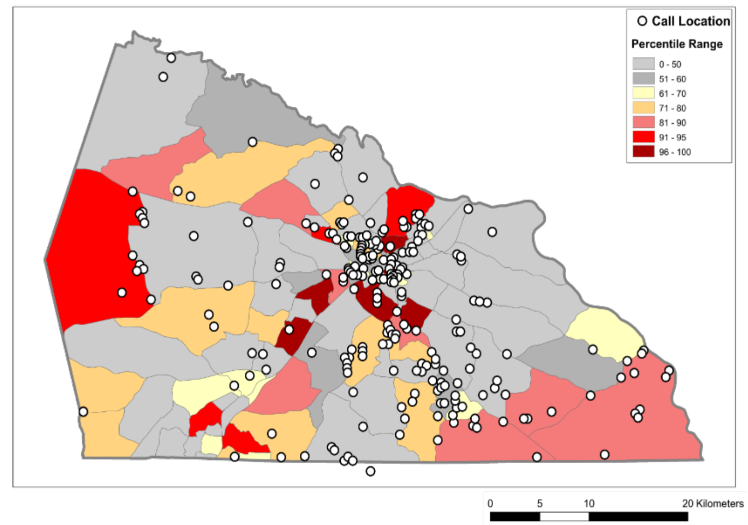
I then used the symbology display under layer properties to set the data classification to manual intervals, and the number of classes to seven. I then set the break values at 50, 60, 70, 80, 90, 95, and 100 to mirror the color-coding scheme on the EPA’s EJ Map tool. I manually configured the color ramp so that it more closely resembled the EPA’s color-coding scheme for sake of clarity. Light grey is less than 50th percentile, darker grey is 51st through 60th percentile, yellow is 61st through 70th percentile, peachy orange is 71st through 80th percentile, 81st through 90th percentile is coral, 91st through 95th percentile is bright red, 96th percentile and above is deep crimson. I applied this to each of the three indicators (Figure 8).

Figure 8 - Maps of EJ Screen Indicators

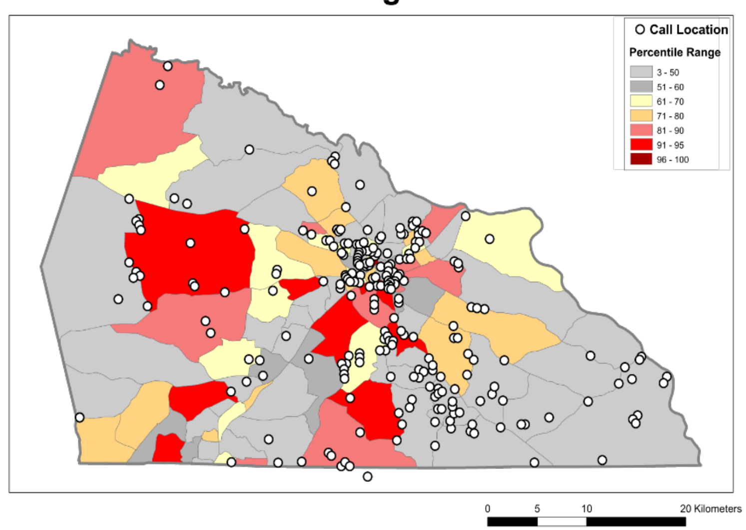
People of Color



Low Income

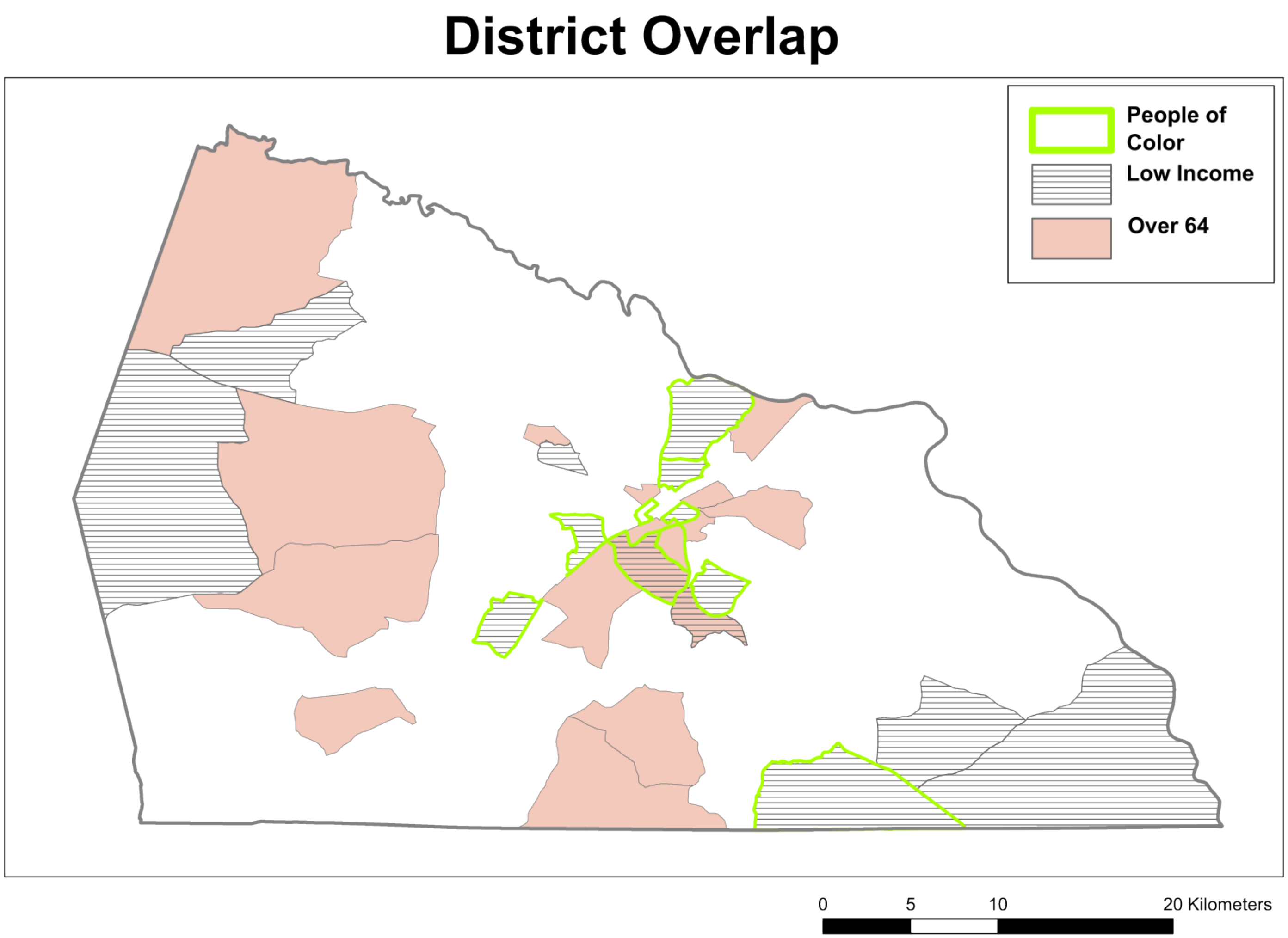


Over Age 64



For each of the EJ Screen indicator maps, I selected the block groups that were above the 80th percentile and had at least one call plotted within their boundaries and created a new layer from those selections. Since several of the districts were above the 80th percentile for more than one indicator, I configured my display symbology so that I could determine exactly which districts were "overlapping." I set the people of color selection layer to a neon green outline with no fill, the low income selection to a line fill, and the over 64 selection layer to a light red (Figure 9). The transparency of the first two layers allowed me to see through them so that I could then select the districts with overlapping criteria and create a fourth selection layer from it. One census block group was labeled a "triple threat" as it was above the 80th percentile for people of color, low income households, and residents over 64. I now had the polygons needed to get accurate counts of the number of calls that took place in areas that were more likely to experience environmental injustice. I used each selection layer to clip my call data points which caused ArcGIS to create a new layer of points and assign those points sequential object ID numbers. To get the point count I opened the attribute table of the clipped point layers and scrolled down to the last entry and recorded the object ID. I then totaled these counts and subtracted the number of overlapping calls and the number of triple threat calls to get an accurate number of calls that took place in areas that are sensitive to at least one EJ Screen indicator.

Figure 9 - Map of Overlapping EJ Screen Areas



CHAPTER III: RESULTS

9-1-1 Call Volume and Distribution

After sorting all call data from the initial online records request and incorporating the additional data from the "wild card" searches, I was able to begin analyzing call volume and distribution across study years as well as the duration of each event. Only four years had flooding events that involved water rescues from pluvial flooding: 2015, 2017, 2018, and 2020. In recent years, calls for flood rescue associated with a pluvial flooding event increased in number and occurred at a wider geographical range across Rowan County, North Carolina, compared to the calls closer to the baseline year.

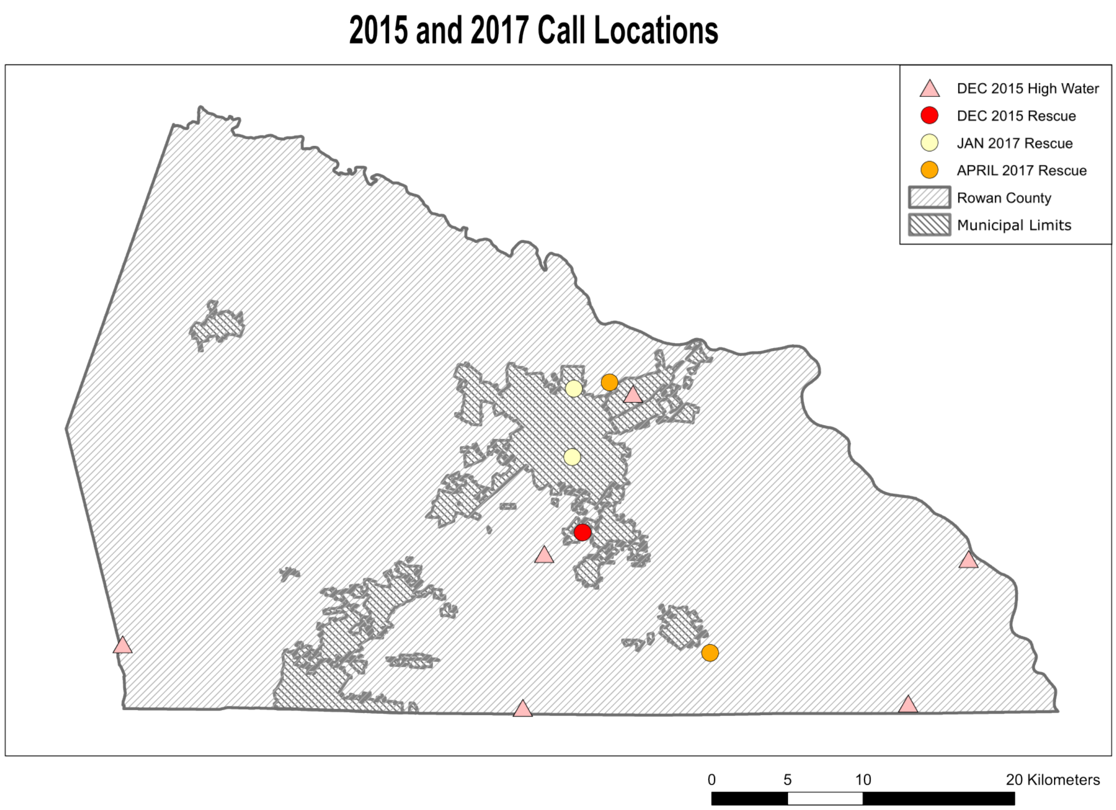
Table 2 - Synopsis of Flood Call Volume

Event Month & Year	Calls Per Event
December 2015	7
January 2017	2
April 2017	2
August 2018	32
September 2018	67
February 2020	38
May 2020	5
August 2020	17
November 2020	90

2015 and 2017

The first event that met all inclusion criteria was the only call for the year 2015. Six calls for high water and one rescue call came in between 10:41 and 16:20 on December 30, 2015. The next two qualifying events were in 2017. On January 23, 2017, at 03:46 a call came in for water rescue inside the city limits of Salisbury. A little over an hour later, a second call came in for water rescue at 04:52. These were the only two calls for the January 2017 event. On April 24 of 2017, two calls came in for water rescue. The first call was received at 07:16 and the second came a few hours later at 10:00. All calls from 2015 and 2017 were mapped together (Figure 10).

Figure 10 - Map of 2015 & 2017 Flood Calls



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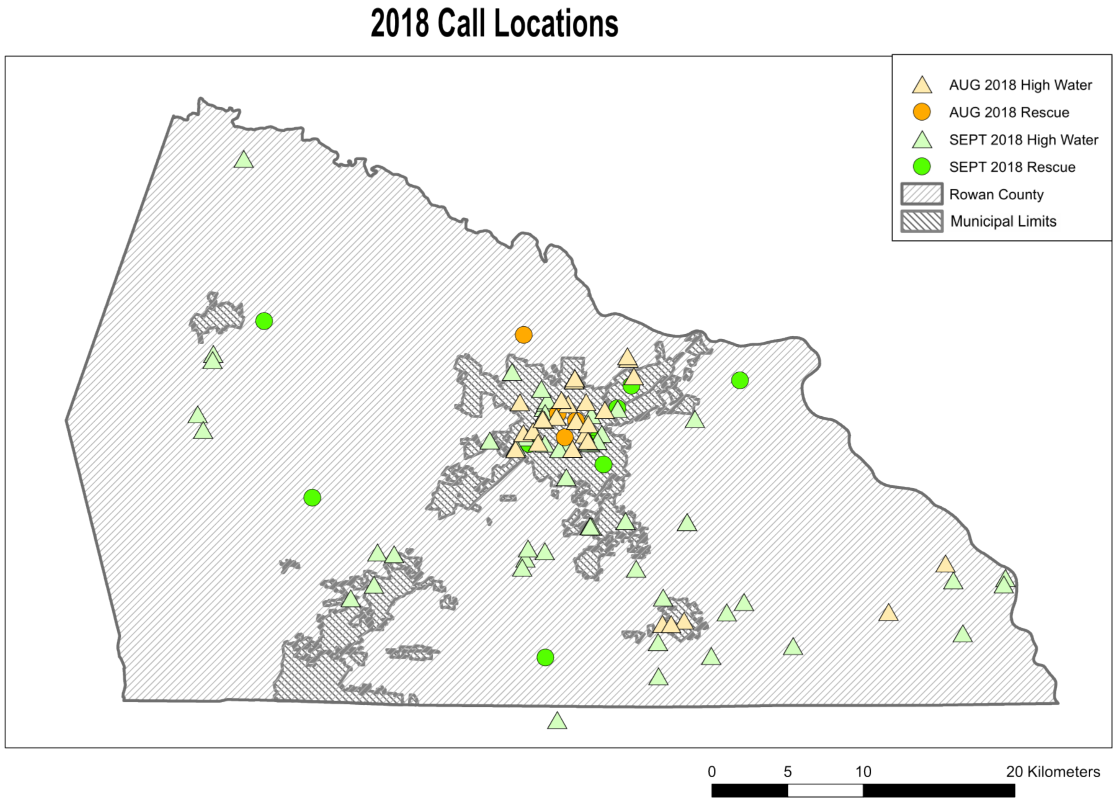
2018

2018 marks a turning point in the call volume for water rescues and high water calls in Rowan County. Two events, one in August and the other in September, generated a combined total of 99 calls. This is also the first time that the data showed an event spanning multiple days. The first of 28 calls related to high water came in on August 1, 2018, at 18:51 and the last call reporting high water was received at 18:35 on August 3, 2018. Across that same span of time, four calls for water rescue rolled in between 18:51 on August 1 and 17:38 on August 3, 2018. Lasting 47 hours and 45 minutes, this is the longest event in the entire study.

Six weeks later on September 16, 2018, at 17:07, the first of ten water rescue calls was received, and calls for high water soon followed. All 57 high water calls were received between 17:59 and 23:03 on September 16. The last of the rescue calls did not come in until 15:52 the next day. Figure 11 shows the map of all 2018 study- related calls. When comparing Figure 10 to Figure 11 it is easy to see that the greatest concentration of calls was inside municipal limits, mainly the county seat of Salisbury. 2020's calls, however, follow a different pattern.

Figure 11 - Map of 2018 Flood Calls



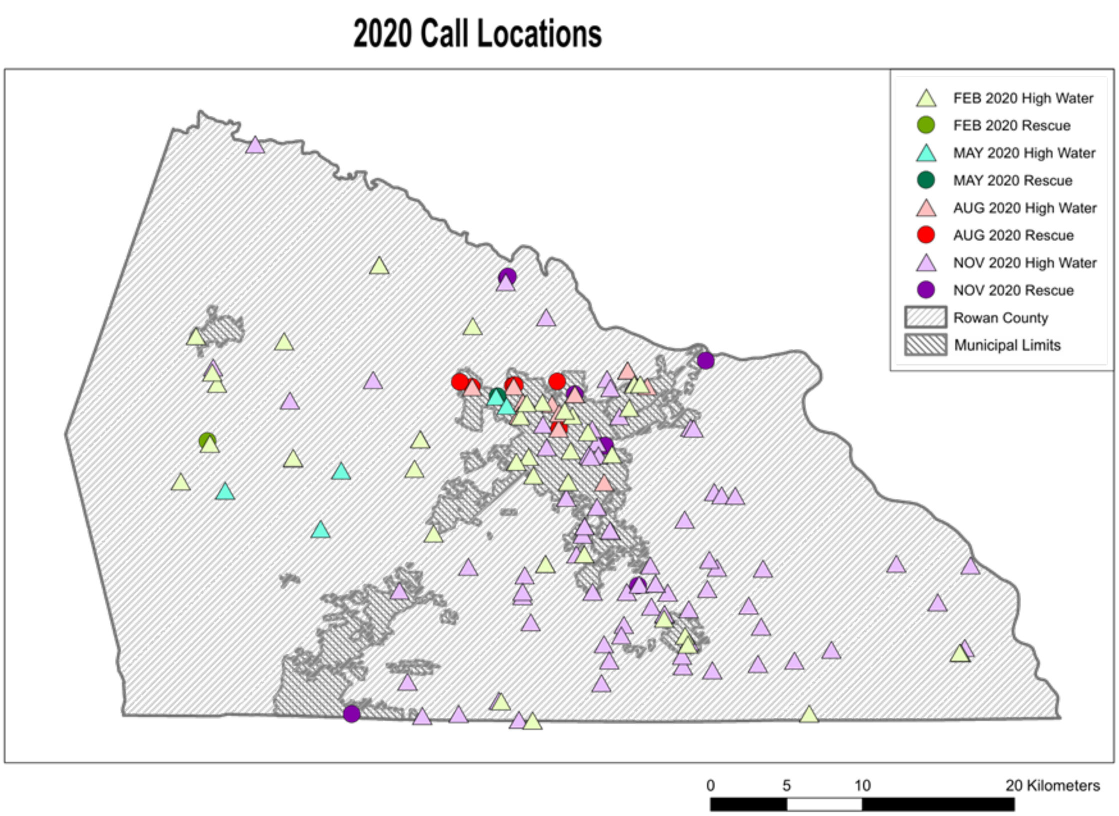
2020

Not only did 2020 yield more calls across a wider geographic range, but there were also more events that met study criteria than in previous years. In 2020, there were a total of 151 high water and rescue calls spread across four separate events. On February 6, 2020, 37 high water calls were received between 12:11 and 16:57. The sole water rescue call for this event came in at 15:42 that same day. May 24, 2020, saw five high water calls between 18:54 and 19:29 and one rescue call at 19:04. Lasting a mere 35 minutes, this is the shortest event in the entire study.

August of 2020 saw another multi-day event which began on the 31st at 15:22 when the first of 11 high water calls was received. The last high-water call came in just before midnight that same day. The first rescue call came in at 15:52 on August 31, 2020, and five more would follow before 15:22 the next day, making the total event 24 hours long.

November of 2020 was the event with the highest call volume in the whole study, and was the second longest event, clocking in at 32 hours and 13 minutes. At 07:26 the first of 83 high water calls resulted from flooding in downtown Granite Quarry, North Carolina. Rescue calls started an hour and a half later at 08:44. A total of seven rescue calls would be received between the morning of the 12th and 15:40 on the 14th. The last high-water call came in at 14:05, also on the 14th. The total call volume for 2020 was 151 calls, which is 1.37 times the total from 2015, 2017, and 2018. Figure 12 shows the calls received in 2020 were more spread out over the county and a much higher portion of calls were outside city limits than in years 2015, 2017, and 2018.

Figure 12 - Map of 2020 Flood Calls



Land Cover Analysis

There are fifteen land-cover categories tracked by the National Land Cover Database: open water, developed open space, developed low intensity, developed medium intensity, developed high intensity, barren land, deciduous forest, evergreen forest, mixed forest, shrub/scrub, herbaceous, hay/pasture, cultivated crops, woody wetlands, and emergent herbaceous wetlands.

Between 2011 and 2021, Medium Intensity Developed space increased by 15.87% and High Intensity Developed space increased by 16.13%. Barren Land increased by 213.52%. However, the sum of these changes amounts to a mere 6.03 square kilometers of land (Table 3).

The largest loss of land-cover type by square kilometer was Deciduous Forest, which dropped from 405.71 km² to 393.41 km², which translates to 12.30 km² having been converted to some other land-cover type. The largest gain by square kilometer was Shrub/Scrub by 9.64 km².

Table 3 - County-Wide Land Use Changes

Rowan County	**2011**	**2021**	**% Type Change**
NLCD Class	square km	square km	
Open Water	32.62	31.89	-2.25%
Developed, Open Space	131.97	131.64	-0.25%
Developed, Low Intensity	76.13	77.12	1.31%
Developed, Medium Intensity	20.67	23.95	15.87%
Developed, High Intensity	9.31	10.81	16.13%
Barren Land	0.59	1.84	213.52%
Deciduous Forest	405.71	393.41	-3.03%
Evergreen Forest	104.13	107.15	2.90%
Mixed Forest	104.81	106.79	1.89%
Shrub/Scrub	17.44	27.08	55.26%
Herbaceous	30.28	26.33	-13.04%
Hay/Pasture	304.09	294.90	-3.02%
Cultivated Crops	105.91	110.41	4.25%
Woody Wetlands	12.03	12.20	1.46%
Emergent Herbaceous Wetlands	1.29	1.43	11.13%

Iterative buffer analysis yielded similar results with gains and losses of cover types being small compared to the total area analyzed, and a definitive pattern was hard to pin down. However, when looking at the reverse-engineered areas that were classified as one of the four developed land-cover types, I was able to start making some sense of it all (Tables 4, 5, 6, & 7). Of the total areas classified as High and Medium Intensity Development in 2021, only 86% of that area was classified as High or Medium Intensity Development in 2011 (Tables 6 & 7). This means that 14% of those areas were converted from lower density development or a natural land-cover type like Herbaceous or Deciduous Forest. Over 98% of the area occupied by Open Development and Low Intensity Development in 2021 was classified as such in 2011 (Tables 4 & 5).

Table 4 - Reverse Engineering Analysis of 2021 Developed, Open Space.

NLCD Classification	2011 Percentage
Developed, Open Space	98.35%
Hay/Pasture	0.69%
Deciduous Forest	0.48%
Cultivated Crops	0.16%
Evergreen Forest	0.11%
Herbaceous	0.09%
Mixed Forest	0.08%
Shrub/Scrub	0.02%
Open Water	0.00%
Barren Land	0.00%

Table 5 - Reverse Engineering Analysis of 2021 Developed, Low Intensity.

NLCD Classification	2011 Percentage
Developed, Low Intensity	97.16%
Developed, Open Space	0.83%
Hay/Pasture	0.81%
Deciduous Forest	0.54%
Cultivated Crops	0.22%
Evergreen Forest	0.18%
Herbaceous	0.18%
Mixed Forest	0.06%
Shrub/Scrub	0.02%
Barren Land	0.01%
Open Water	0.00%
Woody Wetlands	0.00%

Table 6- Reverse Engineering Analysis of 2021 Developed, Medium Intensity.

NLCD Classification	2011 Percentage
Developed, Medium Intensity	85.90%
Developed, Open Space	7.04%
Developed, Low Intensity	2.42%
Hay/Pasture	1.65%
Deciduous Forest	1.12%
Herbaceous	0.58%
Evergreen Forest	0.56%
Cultivated Crops	0.43%
Mixed Forest	0.14%
Emergent Herbaceous Wetlands	0.05%
Barren Land	0.05%
Shrub/Scrub	0.03%
Open Water	0.02%

Table 7 - Reverse Engineering of 2021 Developed, High Intensity.

NLCD Classification	2011 Percentage
Barren Land	0.04%
Cultivated Crops	0.13%
Deciduous Forest	1.06%
Developed, High Intensity	86.11%
Developed, Low Intensity	5.68%
Developed, Medium Intensity	0.91%
Developed, Open Space	1.56%
Emergent Herbaceous Wetlands	0.13%
Evergreen Forest	0.64%
Hay/Pasture	1.89%
Herbaceous	1.51%
Mixed Forest	0.12%
Open Water	0.15%
Shrub/Scrub	0.06%

When comparing the 1.5-km buffer areas' impervious surface percentages to the county as a whole, I found that there was a clear difference between the two. The county's impervious area increased from 17.55% to 17.94% between 2011 and 2021. The 2018 1.5-km buffer area's impervious surface increased from 29.33% to 29.82% (Table 8). The 2020 1.5-km buffer area's impervious surface also increased from 24.91% to 25.41% (Table 9). The buffer area's impervious surface was significantly higher than the county at large's in both the baseline and event years.

Table 8 - 2018 Iterative Buffer Analysis vs. County Wide Changes in Land Use.

2018 Calls: Iterative Buffer Analysis % Change from Baseline to Event Year					**Entire County Change Over Same Time Period**
NLCD Land Type	1 km Buffer	1.5 km Buffer	2 km Buffer	2.5 km Buffer	
Open Water	-13.00%	-10.07%	-6.39%	-4.35%	-1.68%
Developed, Open Space	-0.42%	-0.15%	-0.03%	-0.14%	-0.30%
Developed, Low Intensity	0.44%	0.68%	0.86%	0.74%	0.54%
Developed, Medium Intensity	7.40%	8.72%	9.78%	10.16%	13.33%
Developed, High Intensity	6.11%	7.59%	8.52%	9.08%	13.54%
Barren Land	109.38%	241.82%	234.57%	214.63%	112.29%
Deciduous Forest	-1.56%	-0.84%	-0.95%	-0.99%	-1.51%
Evergreen Forest	-2.43%	-1.91%	-2.77%	-3.01%	-1.16%
Mixed Forest	1.82%	1.90%	2.65%	2.73%	2.25%
Shrub/Scrub	100.31%	74.54%	68.93%	71.42%	60.77%
Herbaceous	-29.88%	-33.62%	-28.49%	-26.83%	-20.53%
Hay/Pasture	-3.03%	-2.97%	-2.93%	-3.01%	-2.84%
Cultivated Crops	5.91%	4.93%	4.71%	5.33%	4.66%
Woody Wetlands	2.29%	1.68%	0.89%	0.68%	1.60%
Emergent Herbaceous Wetlands	-22.16%	-10.93%	3.30%	7.05%	-3.08%

Table 9 - 2020 Iterative Buffer Analysis vs. County Wide Changes in Land Use.

2020 Calls: Iterative Buffer Analysis % Change from Baseline to Event Year					**Entire County Change Over Same Time Period**
NLCD Land Type	1 km Buffer	1.5 km Buffer	2 km Buffer	2.5 km Buffer	
Open Water	-5.56%	-4.82%	-4.02%	-5.40%	-2.25%
Developed, Open Space	-0.54%	-0.31%	-0.17%	-0.21%	-0.25%
Developed, Low Intensity	0.67%	0.88%	1.16%	1.13%	1.31%
Developed, Medium Intensity	9.33%	11.14%	13.17%	13.76%	15.87%
Developed, High Intensity	8.71%	11.95%	15.83%	16.08%	16.13%
Barren Land	115.77%	130.48%	143.65%	180.52%	213.52%
Deciduous Forest	-2.33%	-1.86%	-1.94%	-2.30%	-3.03%
Evergreen Forest	2.24%	4.57%	3.23%	3.10%	2.90%
Mixed Forest	2.08%	3.22%	2.60%	2.43%	1.89%
Shrub/Scrub	30.33%	13.34%	14.94%	27.23%	55.26%
Herbaceous	-13.67%	-19.54%	-13.70%	-13.04%	-13.04%
Hay/Pasture	-3.52%	-3.42%	-3.08%	-3.09%	-3.02%
Cultivated Crops	5.05%	4.01%	3.28%	3.59%	4.25%
Woody Wetlands	1.88%	0.86%	0.55%	0.15%	1.46%
Emergent Herbaceous Wetlands	-6.28%	3.44%	8.91%	14.67%	11.13%

Height Above Nearest Drainage

The GIS analysis of the highest HAND value shows that each event registered at least one call with an elevation of higher than 2.5 meters relative to the closest branch of the local drainage system. The November 2020 event, which had the most calls by far, also held the record for highest HAND value (Table 10).

Table 10 - Height Above Nearest Drainage Results.

Event	Average HAND Value (m)	% of Calls ≥ 2 m Above Nearest Drainage	Highest HAND Per Event (m)
Dec 2015	0.72	14.30%	2.91
Jan 2017	1.35	50.00%	2.69
Apr 2017	2.02	50.00%	4.04
Aug 2018	0.74	18.75%	3.77
Sep 2018	0.57	10.45%	3.28
Feb 2020	0.62	13.56%	2.81
May 2020	1.26	16.67%	3.15
Aug 2020	0.22	5.88%	2.91
Nov 2020	0.75	16.67%	4.38

Weather Events

Precipitation plays a key role in flooding. I expected to find an increase in pre-event precipitation and an increase in precipitation during flooding events. I also expected that call volume would be higher during heavier rainfall events. While an exact linear relationship between call volume and precipitation cannot be established, higher precipitation events do seem to be correlated with more calls for flood rescue.

What is really interesting, though, is the data from the IDF analysis. I initially thought I had found a pattern of record rainfall, as expected. However, I quickly realized that I had not yet converted the IDF chart from inches to centimeters. Once observed rainfall amounts and IDF values were in the same unit of measurement, I was surprised to find that most of the flooding events in the study were associated with 1- to 5-year recurrence interval rainfall events. This held true for the data preceding each event, and the observed rainfall during each event. The May 2020 event was the only one associated with a 100-year event. The time between the first call and the last was only 35 minutes, and during that time Rowan County received 5.69 cm of rain (Table 11).

Table 11 - Intensity, Duration, Frequency analysis of rainfall preceding each event.

Event	12/30/2015	1/23/2017	4/24/2017	8/1/2018	9/16/2018	2/6/2020	5/24/2020	8/31/2020	11/12/2020
2 days prior	N/A	N/A	1 year	3.5 year	7.5 year	3.5 year	N/A	1 year	3.5 year
7 days prior	N/A	N/A	N/A	1 year	3.5 year	2 year	10 year	N/A	1.5 year
30 days prior	1 year	N/A	N/A	3.5 year	N/A	N/A	3.5 year	2 year	N/A
60 days prior	2 year	N/A	N/A	1 year	10 year	N/A	1 year	5 year	3.5 year
	▲-------------------------Recurrence Interval of Preceding Rainfall for Each Event------------------------- ▲								

The flood gauge data from the USGS yielded some interesting results. I expected to find a pattern of call volume that rose and fell in a pattern that was similar to the gauge's data, but that did not always hold true (Figure 13).

The August 1, 2018, event seemed to track with the flood gauge. The river reached 3.66 meters at 16:45 on August 1st, the first call for service came in a little over two hours later at 18:51, and calls would continue to come in steadily until midnight. Calls were sporadic throughout the next day as the waters began to recede. The river rose even higher to 4.42 meters at 15:00 on August 3rd and a few more calls came in between 17:38 and 18:35.

On September 16, 2018, at 17:59,the river stage was at 1.5 meters. As calls came in through the night and into the next day, the river steadily rose but would not crest until 08:00 on the 18th, 16 hours after the last call.

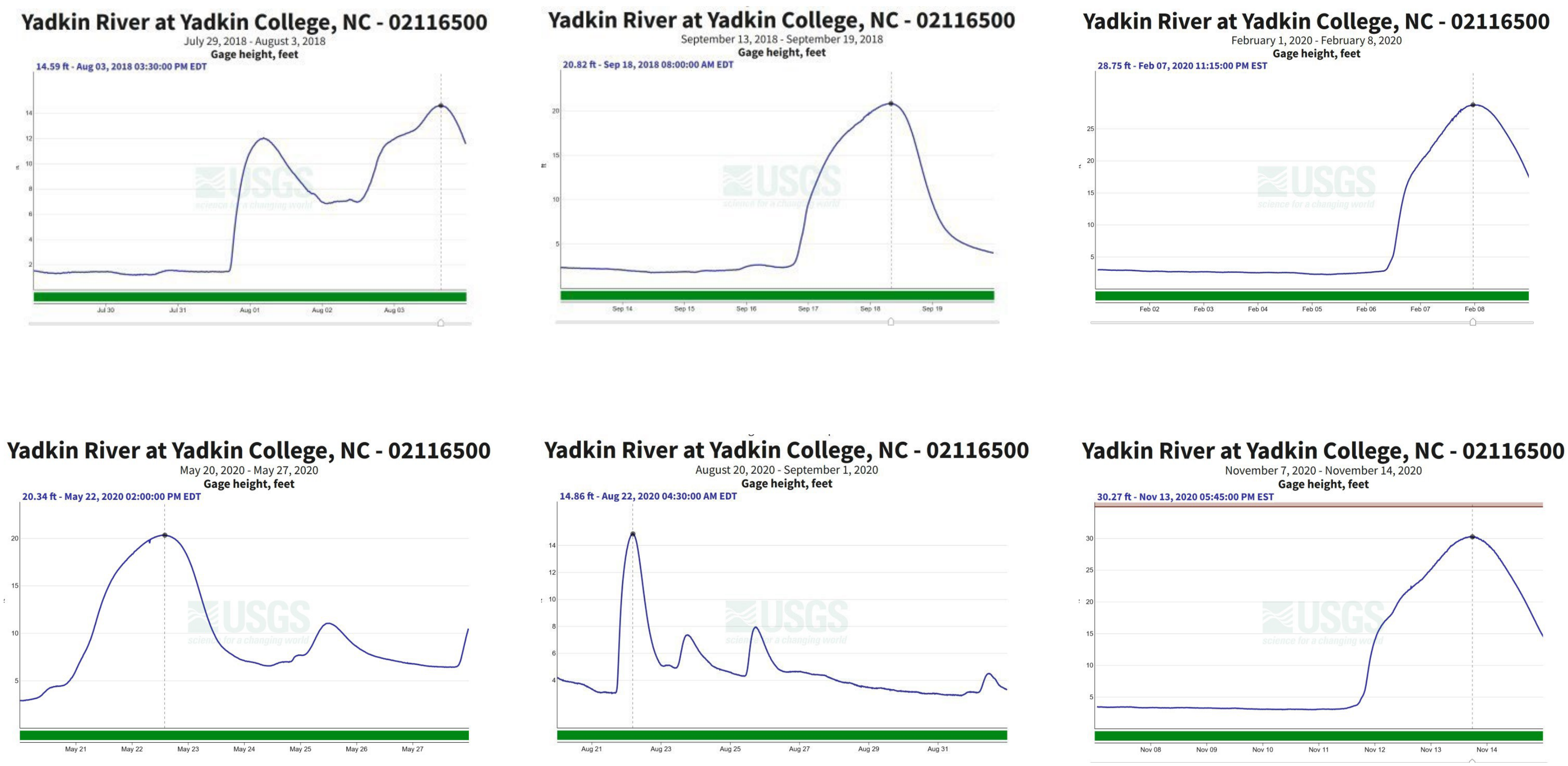
On February 6, 2020, at 11:13, the first flood call came into the 9-1-1 center. The Yadkin River had begun to rise but had yet to reach 1.5 meters. The river had reached 3.96 meters by the time the last flood call came in at 16:58. The river would not crest until two days later at 8.76 meters on Feb 8th.

The May 2020 event started at 18:54 on the 24th. The river had crested more than 48 hours prior at 14:00 on the 22nd. The Yadkin College gauge showed a peak height of 6.2 meters. By the time calls for flood rescue began to come in, the river had gone back down to 1.98 meters, hardly flood levels. This does, however, coincide with a 10-year rainfall event taking place in the 7 days prior to the event.

August 2020 showed a pattern of call volume versus river gauge height that was even more out of sync. Calls for service started at 15:22 on the 31st when the river was measuring less than 1.25 meters 9 days earlier, on the 22nd, the river had reached nearly 4.57 meters, but had sharply declined shortly thereafter and water levels remained low from the 27th through the 31st.

On November 12, 2020, at 07:26, the first of 90 total calls began coming in due to flooded roads and flooded homes. 70 of those calls would be received by noon on the 12th. The river had begun to rise around 17:00 the evening before and had risen to over 5.5 meters at the time of the first call. The river would continue to rise until it peaked at 17:45 on the 13th, reaching 9.14 meters.

Figure 13 - USGS Flood Guage Graphs



Social Justice Dimensions

During the study period, a total of 261 calls were recorded. 46% of those took place in an area that was sensitive to one or more of the three chosen EJ Screen indicators (Table 12).

Table 12 - Results of EJ Screen Indicator analysis.

EJ Screen Indicator	Low Income	Over 64	People of Color	At Least 2 Indicators	All Three Indicators
Number of Calls	69	60	45	49	5
Percentage of Total Calls	26%	23%	17%	19%	2%

CHAPTER IV: DISCUSSION AND CONCLUSIONS

Discussion

The purpose of this study was to analyze patterns of urban flooding in Rowan County in the hopes of gaining insight into the causes of a few rain events that resulted in what many of my Rowan Rescue Squad colleagues characterized as unusually high call volume. The maps and charts produced by this study paint a clear picture of an uptick in call volume and a growing number of calls happening outside of city limits in Rowan County. Increased occurrences of intense storms seem to contribute to producing more flooding calls in locations that fell farther outside municipal limits in the latter years of the study period.

9-1-1 Call Volume

Question 1. What are the observed trends in water rescue events in Rowan County for years 2011-2021?

Hypothesis 1. I expect to find an increase in call volume for individual events as well as more frequent events in the latter years of the study period.

Indeed, I did find more calls and more frequent events in the years 2018 and 2020 than I did in 2015 and 2017. Using 9-1-1 call data to map pluvial flooding is not without precedent and has been shown to be a useful tool to fill in knowledge gaps about pluvial flooding (Brody et al. 2021, Oliva and Olcina 2023), but it is also not without limitations. As mentioned before, the Emergency Medical Dispatch system codes and dispatches calls for service based on how the caller answers the dispatcher’s questions. During an emergency, people do not always communicate clearly, which can lead to calls initially being dispatched as something unrelated to the actual problem at hand. This can and certainly does happen as my personal experiences responding to emergency calls has proven. The aforementioned call that I was personally on but that was not captured in my initial data query was subsequently not pulled into either of the "wild card" searches done by Chief Phil York on my behalf. We spoke about that, and he explained that since the call originated in Davidson County's 9-1-1 system and was transferred to us when it was determined Rowan Emergency Services would have better access to the patient, it could have affected the way the call was coded and stored in the database. Oliva and Olcina (2023) noted similar troubles with their data, stating that callers are not always the most accurate narrators and therefore the initial coding of the dispatched call may be incorrect. Additionally, I did not search for all calls coded "High Water" during the study period, as I was advised that would generate too much data to parse. So while I feel my methodology for including or excluding calls was rational, it is possible given more time or a better tool than my having to read through the notes of literally thousands of calls to sort them properly, I may have been able to provide more consistent flooding data across all study years, and not just the few that were associated with flood rescue calls. Additionally, changes to dispatching practices and call coding methodologies could have contributed to more calls being captured and coded as "flood rescue" rather than more generic terms like "rescue assignment" or "fire department service assignment", which came up in the raw unsorted call data quite frequently.

9-1-1 Call Distribution and Land Cover Changes

Question 2. What are the controls on the spatial patterns of water rescues in Rowan County for years 2011-2021?

Hypothesis 2. I expect to find a pattern of increased call volume over a wider area of the county. I expect to find a pattern of land use change that contributes to the increased call volume and more widely distributed call locations.

I was anticipating that high and medium intensity development had supplanted large swathes of deciduous, evergreen, and mixed forests, but that was not quite the case. The common thread across the changes in land cover in the whole county and in each of the iterations of the buffer analysis is that there were only modest increases in high and medium intensity development. By square kilometer, the land-cover changes noted were minor when studied by individual classification. I expected to find evidence that more than 2,000 acres of land had been made "shovel ready", but the analysis I was able to perform did not support that, as I lack location data on those projects.

What is significant is my comparison of the county's impervious surface to that of the 1.5-km buffer area. Liu, Li, and Wang (2021) found that as little as a 20% to 25% impervious surface area was associated with a transition from minimal to significant alterations in runoff patterns in smaller watershed basins. Reduced evapotranspiration in urban areas is associated with an increase in pluvial or flash flooding in developed landscapes (Boggs and Sun 2011). The land area within the 1.5-km buffer areas contains 7% to 12% more developed area and therefore less vegetation, and I feel confident that this translates to a meaningful loss of evapotranspiration capacity for those areas most affected by flooding.

Weather and Pluvial vs. Riverine Flooding

Question 3. What meteorological conditions are associated with water rescue events in Rowan County for years 2011-2021?

As expected, the number of calls related to urban flooding were much higher in the later years of the study period than in the first years. Cross-referencing my 9-1-1 call data with precipitation data collected at various time resolutions showed that, of the eight events in the study, only one was associated with a 100-year rainfall event.

Stream gauge data seemed to conform more closely to my expectations, but not entirely. While many of the study events were associated with elevated water levels in the Yadkin River, not all of them were. The May 2020 and August 2020 events seemed to occur well after the waters of the Yadkin had returned to normal volume, and these events did not coincide with significantly intense rainfall. This suggests that many of the events during the study were not purely due to pluvial flooding, or that riverine flooding was occurring at the same time as the events in the study. The absence of recorded flood stage during the May 2020 and August 2020 events seems to suggest these events were more likely to be mostly or completely caused by pluvial flooding.

Social and Environmental Justice

Question 4. What socio-economic conditions may be influencing the most heavily impacted areas within the study?

I expected to find that a large portion of the calls within the study took place in an area that was sensitive to at least one of the three chosen EJ Screen indicators. Nearly half of the calls met this criterion and one out of every five calls happened in an area that was sensitive to two or three of the EJ Screen indicators. This finding underscores the need to continue studying the connections between socio-economic factors and vulnerability to natural hazards like flooding. It also underscores the need for targeted outreach programs to these communities that include messaging tailored to each community and partnerships with community leaders.

Confounding Factors

Increased cellphone use has led to increased 9-1-1 phone calls, both intentional and unintentional. Additionally, it is not uncommon for multiple people to call 9-1-1 in a very short span of time to report the same issue. I attempted to control for duplicate calls by looking at the call notes and the timestamp on each record. Without access to data that is not part of the public records request process, I cannot rule out the possibility that a portion of the increased calls noted in the latter years of this study are partially due to redundancies.

Evapotranspiration capacity is not static throughout the year. With the changing of the season comes ebbs and flows in plant metabolism. Trees that have shed their leaves and stand bare in early February are using much less water than trees with a full canopy attempting to survive in the late August heat (Boggs and Sun 2011, Kim, Band, and Ficklin 2017). Therefore, while many of the events in this study were associated with commonly occurring rainfall events, 1- to 5-year events, those events' impacts were likely influenced not only by impervious surface area but also by the seasonal capacity of the local vegetation to take in water from the soil.

Weather patterns and flood gauge data did not yield clear definitive evidence of purely pluvial flooding events. Additionally, the complex nature of changing land use makes it hard to parse exactly how much of a role development played in influencing these events. I feel I have made a strong argument that it is likely that land use changes played a role in one or more of these events, but in the absence of more sophisticated modeling and simulation programs, I cannot determine the extent to which these events were caused by either altered landscapes or changing weather conditions.

Conclusions

As Rowan County's population grows, more people have the potential to be adversely affected by pluvial flooding. We know that rainfall from more intense cloudburst storms is likely to continue fueling more frequent and more severe pluvial flooding over the next several decades (NC DEQ 2020). Flooding hazards are at the top of the list of concerns for many Rowan County Emergency Management personnel, and rightfully so (AECOM 2019). Investments in infrastructure improvements to manage stormwater and adapt to flooding as well as a greater public awareness of personal risk and appropriate preparedness steps is warranted (Knighton et al. 2021; Kubal et al. 2009). Using citizen-sourced data in general is also becoming a more widely accepted scientific practice (Ortiz et al. 2024) and is in line with the recommendations set forth by the United Nations' Sendai Framework for Disaster Risk Reduction. As sourcing data from ordinary people and developing a bottom-up approach to natural hazards mitigation becomes more widely used, better and more standardized methods of analysis will likely be developed, which could have aided in better defining exactly why there were more calls in 2018 and 2020 and the amount of causation that could be assigned to either heavy precipitation or increases in impervious surface. As more advanced computer modeling and artificial intelligence become available, we may be able to precisely determine the exact proportions of influence that land-cover changes and precipitation intensity have on pluvial flooding.

Greater emphasis needs to be placed on flash flood forecasting and early detection and warning systems, like those established in Charlotte (Konrad, n.d.). Predicting the future relies heavily on the ability to study past events. As Emergency Services works to rise to the challenges of the twenty-first century, accurate 9-1-1 call data will become an increasingly valuable resource for conducting retrospective studies and projecting future trends in rescue services. By anticipating future call scenarios, Emergency Services can better tailor training exercises to prepare for the future needs of a growing population.

The United Nations' Sendai Framework for Disaster Risk Reduction 2015–2030 calls for a shift away from disaster response towards a focus on prevention and mitigation. Knowledgeable citizens make choices that prevent them from becoming injured, disabled, or deceased during a sudden emergency event (Geisler 2018,). Practical Fire Life and Safety

Education (FLSE) programs have significantly decreased the number of fatalities due to house fires across the United States (Huseyin and Satyen 2020). FLSE programs have expanded to cover bicycle safety, proper car seat installation and seatbelt usage, and Halloween safety. I suggest that, given the increased concerns around flooding in North Carolina and Rowan County, specifically (NC DEQ n.d., AECOM 2019), campaigns that focus on spotting flood dangers and "turn around, don't drown" messaging should be the next area of expansion for the FLSE curriculum. Additionally, a greater focus on conducting outreach efforts to historically underserved communities and building relationships with community leaders will become increasingly important so that FLSE personnel can effectively empower community members to take appropriate action in the face of sudden flooding. Flood risk will only increase over the coming decades, and we owe it to ourselves and the communities we serve to prepare for it as thoroughly as possible.

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