STATISTICAL AND SPATIAL ANALYSIS OF HURRICANE-INDUCED POWER OUTAGE AND RESTORATION

A Thesis Presented for the

Master of Science

Degree

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DEDICATION

My thesis is dedicated to my parents, family and friends who taught me that through hard work and perseverance anything is possible.

ABSTRACT

Tropical cyclones (TC) cause billions of dollars in damage to coastal areas in the United States annually. Global climate change is increasing favorable environmental conditions for TCs which produce heavy flooding and precipitation. It is important to understand the communities that will be most affected, and will likely suffer the longest power outages. County-level power outage data from the Department of Energy's Environment for Analysis of Geo-Located Energy Information (EAGLE-I) were used to analyze the relationships of environmental and socioeconomic variables on power outage trends, response, and recovery for power outages caused by two North Atlantic Basin hurricanes: Hurricane Florence (September 2018) and Hurricane Sally (September 2020). Hurricane Florence reached Category 4 wind speeds, but ultimately made landfall as a Category 1 along Wrightsville Beach, North Carolina. Hurricane Sally was a category 2 system that made landfall along Gulf Shores, Alabama. A daily average power outage baseline was created from four years of power outage records. From this baseline, power outages were identified that could be attributed to either hurricane. Quasi-Poisson and linear regression models were used to assess relationships between power outage trends, hurricane characteristics, and socioeconomic variables. Kruskal-Wallis tests were used to assess land classification and helped assess whether methods used were suitable for studying hurricane-related power outage trends. Relationships identified within data were found to be inconsistent across both study areas. Analyses of Florence's study area indicated a statistically significant relationship between the number of consecutive days a county experiences power outages and daily average power outage with TC strength and percent of population below poverty. However, in Sally's analyses, the affected county's distance from the TC track was the

only statistically significant variable found across the analyses. This paper analyzes the complex interactions between county level power outages caused by TCs and the influence of socioeconomic variables on them using EAGLE-I data.

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CHAPTER: 1 INTRODUCTION

Tropical Cyclones (TCs) cause billions of dollars in damage annually to the United States Atlantic Coast, leaving millions of people without power for days (Emanuel, 2005; Klotzbach et al., 2018; Pielke et al., 2008). Studies suggest that the impact of TCs on the Atlantic Coast will increase due to coastal population growth, favorable environmental conditions for TCs, and climate change(Hall and Kossin, 2019; van Oldenborgh et al., 2017). Climate change causes slower-moving, yet more intense, TCs in the North Atlantic Basin. Models predict an increased likelihood of high-precipitation TC events in the decades to come (Ting et al., 2019). Slower-moving TCs produce high volumes of precipitation (Hall and Kossin, 2019; van Oldenborgh et al., 2017), which leads to increased risk, severity, and duration of flooding events. United States (US) coastal counties have seen rapid population growth over the past decade, and report some of the steepest population increases in the country. According to the Census Bureau, in 2016, 94 million people (29% of the U.S. population) live in counties that border the coastline (US Census Bureau, 2020a). Between 2015 and 2016, two of the top twenty-five fastest growing metropolitan areas were in South Carolina (Myrtle Beach and Charleston)(US Census Bureau, 2020b). Counties along the gulf coast have also seen significant growth. The 2020 Decennial Census, found Baldwin county in Alabama to be the 7th fastest growing metropolitan area in the US (Brown, 2021).

The simultaneous increase in coastal population and costly hurricane impacts due to climate change motivates my thesis. It is important to better understand the social dynamics of TC recovery to strengthen community resiliency (Thompson et al., 2012). In addition to widespread flooding, widespread power outages are also commonly observed in communities

after TCs. Therefore, the number of power outages is one way to assess TC impact on communities. In the same vein, power outage restoration rates can suggest community recovery.

Not all communities recover from power outages associated with TCs at the same rate. More affluent communities may have access to additional resources, to aid in power outage restoration, which other places may lack. Many studies report a similar trend when examining the impact of COVID-19. Counties with a higher Black population reported more deaths than largely white counties, which was attributed to differences in hospitals or quality of care.TC recovery is inequitable and socially unjust. County-level socioeconomic demographics likely play a role (Duffey, 2019; Mitsova et al., 2018; Wilson, 1999). Previous studies found that areas of low income and unemployment are more susceptible to longer power outage restoration times (Duffey, 2019; Mitsova et al., 2018; Wilson, 1999). It is therefore important to understand how quickly different communities restore power, which communities tend to restore power the quickest, and what factors influence TC recovery time.

My thesis focuses on two recent and devastating TCs: Hurricane Florence (September 2018) and Hurricane Sally (September 2020). Florence impacted the United States East Coast while Sally made landfall along the Gulf Coast. I selected these two TCs because both were slower-moving storms that brought heavy precipitation and flooding who's impact on power outages were recorded in the Department of Energy's Environment for Analysis of Geo-Located Energy Information (EAGLE-I).

1.1 Tropical Cyclone Formation

The atmospheric and environmental dynamics that contribute to TC formation have been studied extensively over the past 60 years (Emanuel, 2018). A tropical cyclone, as defined by the National Oceanic and Atmospheric Administration (NOAA), is a "warm-core non-frontal

synoptic-scale cyclone, originating over tropical or subtropical waters, with organized deep convection and a closed surface wind circulation about a well-defined center" ("Glossary of NHC Terms," 2020). TCs in the North Atlantic Basin begin as low-pressure disturbances in the tropics and intensify in favorable environments (American Meteorological Society, 1968). The tropics in the northern hemisphere are defined as latitudes ranging from 5°N to 30°N. Favorable environmental conditions include warm water (sea surface temperature over 26.5 degrees Celsius) and low wind shear. For a TC to form, a cyclonic low pressure has to occur between 5 and 30 degrees of latitude with seawater temperature over 26.5 degrees Celsius where there is low wind shear (American Meteorological Society, 1968; Elsner and Kara, 1999). Sustained wind speed differentiates classifications of TCs: Tropical Depressions (winds < 33 knots); Tropical Storm (winds 33–64 kn); Hurricanes (Categories 1 and 2 with winds 64–95 kn); and Major Hurricanes (Categories 3 through 5 with winds > 95 kn)("Tropical Cyclone Climatology," 2020). The TC season in the North Atlantic Basin is annually from June and November, with seasonal peaks between August and October (Elsner and Kara, 1999; "Hurricanes - Florida Climate Center," 2020).

1.2 Hurricane Power Outages

Natural and anthropogenic disasters disrupt power to millions of people and cause billions of dollars in damages annually in the US and its Territories. TCs are the most devastating of these disasters, causing an average of 21 billion dollars in damages and disrupting critical infrastructure systems for days (Ting et al., 2019; US Census Bureau, 2020a). Hurricane Florence was one of the most deadly and costly hurricanes to impact the Carolinas and caused 24 billion in damages. Hurricane Florence disrupted power to approximately 1.1 million people and left some without power for up to two weeks (US Census Bureau, 2020b; US Department of

Commerce, 2020). Hurricane Sally caused record-breaking precipitation and flooding along the Gulf Coast. The impact of flooding on the Gulf Coast was made worse by storm surge (Berg and Reinhart, 2021). Extreme precipitation and flooding paired with hurricane-force winds caused over 7.3 billion dollars in damages (Berg and Reinhart, 2021). Flooding damaged roadways and left others impassable. More than 550,000 people lost power, with some experiencing power outages for over two weeks (Berg and Reinhart, 2021; Castor, 2020; Miller and Blanks, 2020) .

CHAPTER 2: RESEARCH QUESTIONS AND OBJECTIVES

Using data provided by EAGLE-I, this thesis analyzes the power outages caused by Florence and Sally and the relationships of socioeconomic variables on power outage recovery time for counties affected by either hurricane. EAGLE-I provides real-time situational awareness capability for electricity, natural gas, coal, and petroleum energy sub-sectors. Previous research found a correlation between power outage restoration response time, poverty metrics (income and unemployment), and precipitation totals (Duffey, 2019; Mitsova et al., 2018).

The objective of this thesis is to analyze power outage trends in coastal counties during hurricanes that cause extreme precipitation. To complete this analysis, three questions will be answered:

1. At the county level, is there a measurable correlation between power outage recovery time and socioeconomic status, and how do these compare across the two study areas?
2. Do counties issued disaster declarations take longer to restore power than counties that do not issue disaster declarations?
3. During extreme precipitation TCs, do impacted counties that share similar socioeconomics in the study areas (North and South Carolina, Florida, Mississippi, and Alabama) reach maximum power outages at similar times after landfall?

CHAPTER 3: LITERATURE REVIEW

3.1 Changing Hurricane Patterns

Multiple atmospheric and environmental factors affect hurricane formation, strength, and tracks (American Meteorological Society, 1968; Elsner and Kara, 1999). Recent literature focuses on the impact of anthropogenic climate change on hurricane development and severity. TC frequency, intensity, and translation speed are among the variables most widely discussed (Emanuel, 2021; Kossin, 2018). Current literature indicates shifts in hurricane characteristics, including an increase in hurricane intensity for the strongest storms in some basins (Elsner 2020) and slower translation speed (Lanzante 2019). There is debate about a potential slowdown in TCs that stall over coastal areas and cause dangerous flooding events (Emanuel, 2021; Goldenberg and Shapiro, 1996). The effects of increased TC precipitation, due to anthropogenic climate change, have already been observed in Hurricanes Harvey (August to September 2017), and Florence (Guikema et al., 2014; Reed et al., 2020; van Oldenborgh et al., 2017). Researchers found that anthropogenic climate change caused a 15% increase in precipitation intensity during Hurricane Harvey and a 4.9 ± 4.6% increase in average inland rainfall during Hurricane Florence (Reed et al., 2020; van Oldenborgh et al., 2017). TCs are likely to cause extreme precipitation and flooding as the climate continues to change (Reed et al., 2020). Guikema et al. (2014) found that total rainfall was the best predictor of power outages during TCs that had slower translation speeds.

3.2 Coastal Populations

Coastal populations have been steadily increasing during the past decade. While these areas are increasing in popularity, they are also increasing in vulnerability to climate change and natural

disasters. Marsooli et al. (2019) found that on average sea level has risen 8 to 9 inches since 1880 and continues to increase today. Current best-case scenario climate models predict global sea level to rise at least one foot by 2100 (Lindsey, 2018). Coastal communities will resultantly become even more vulnerable to the impact of high precipitation TCs and storm surge (Marsooli et al. 2019). Flooding is already one of the leading causes of extended power restoration time, increasing population in coastal areas and higher risk of flooding events will worsen the impact. Klotzbach et al. (2018) reported that 2006 to 2017 had relatively few strong TCs that impacted the contiguous United States (CONUS). People and investors likely did not feel threatened by recent TC activities and a high density of people, businesses, and buildings in coastal areas resulted. Hurricane Harvey and Irma highlighted what damage TCs that are intensified by anthropogenic climate change can do to population centers. Both TCs totaled over 125 billion dollars in damage (Hurricane Costs). Florida, the state with the most hurricane landfalls in recorded US history, had been preparing for Irma's landfall for days but still lost power to 6.7 million people (Chakalian et al. 2019; Jagger and Elsner 2006; US Department of Commerce 2020; Blake et al. 2005). Over 100K people remained without power a week after landfall (Chakalian et al., 11/2019; Jagger and Elsner, 2006; US Department of Commerce, 2020). With the increased likelihood that TCs will be impacting the US coasts, it is important to understand the communities that are most affected, and will likely suffer the longest power outages.

3.3 Electric Restoration Research

Current literature discusses advances in models used for predicting hurricane damage (Guikema et al., 2014). Many of these studies use maximum wind speed, total rainfall, and land cover as explanatory variables to predict the number of power outages, while more recent studies have been examining the effect of flooding into delayed power restoration (Duffey, 2019; Guikema et

al., 2014; Zhang et al., 2018). Research indicates that increased urbanization exacerbates flooding and rainfall caused by TCs (Zhang et al., 2018). Flooding has also been found to increase power restoration times, due to inaccessibility to affected infrastructure (Duffey, 2020, 2019). Inland flooding caused much of the economic loss of hurricanes that made landfall between 2001 and 2014 (Czajkowski et al., 2017). Current research has indicated that low-income populations and minorities are more likely to be found in areas that are at elevated risk from flooding and power restoration times (Duffey, 2019; Mitsova et al., 2018).

CHAPTER 4: STUDY AREA AND DATA

4.1 Study Area

Coastal states within 100 miles of where hurricanes Florence or Sally made landfall were selected as the study area. Florence made landfall as a Category 1 hurricane on September 14, 2018, in New Hanover County, North Carolina. As shown in Figure 1, 100 counties in North Carolina and the 47 counties in South Carolina were used as the counties of interest for Florence. Sally made landfall as a Category 2 hurricane on September 16, 2020 in Baldwin county, Alabama. All 62 counties in Alabama and 82 in Mississippi, and 22 counties within the Florida panhandle region were chosen as the study area for Sally (see Figure 1). The majority of the damage done to counties after Sally's final landfall in Florida fell within the panhandle region (Berg and Reinhart, 2021).

4.2 Data

Power outage data needed to conduct this study is provided by the Department of Energy (DOE). It is generated by the DOE's electrical grid situational awareness tool, EAGLE-I. EAGLE-I parses and stores near real-time power outage information for 90% of the US. It collects open-source data containing the number of electric customers without power at the county level at fifteen-minute intervals from over 400 electric utility websites at varying resolutions (county, zip code, and latitude/longitude) (Bhaduri et al., 2021). The data are aggregated to either county, state, or Federal Emergency Management Agency (FEMA) regions. This power outage database contains data from 2014 to present. However, coverage of the United States prior to 2017 contains only 70% coverage of utility customers. The dataset created by EAGLE-I is a proprietary database that is not available to the public.

The county level socioeconomic data, race and the percent of the population below poverty level were obtained through the 2019 American Community Survey (ACS). Hurricane track and intensity metrics, seen in Figure 1, were obtained through the National Hurricane Center (NHC). County disaster declaration status data for TCs Florence and Sally were obtained through the Federal Emergency Management Agency (FEMA). A description of these data can be found in Table 1 and Table 2.

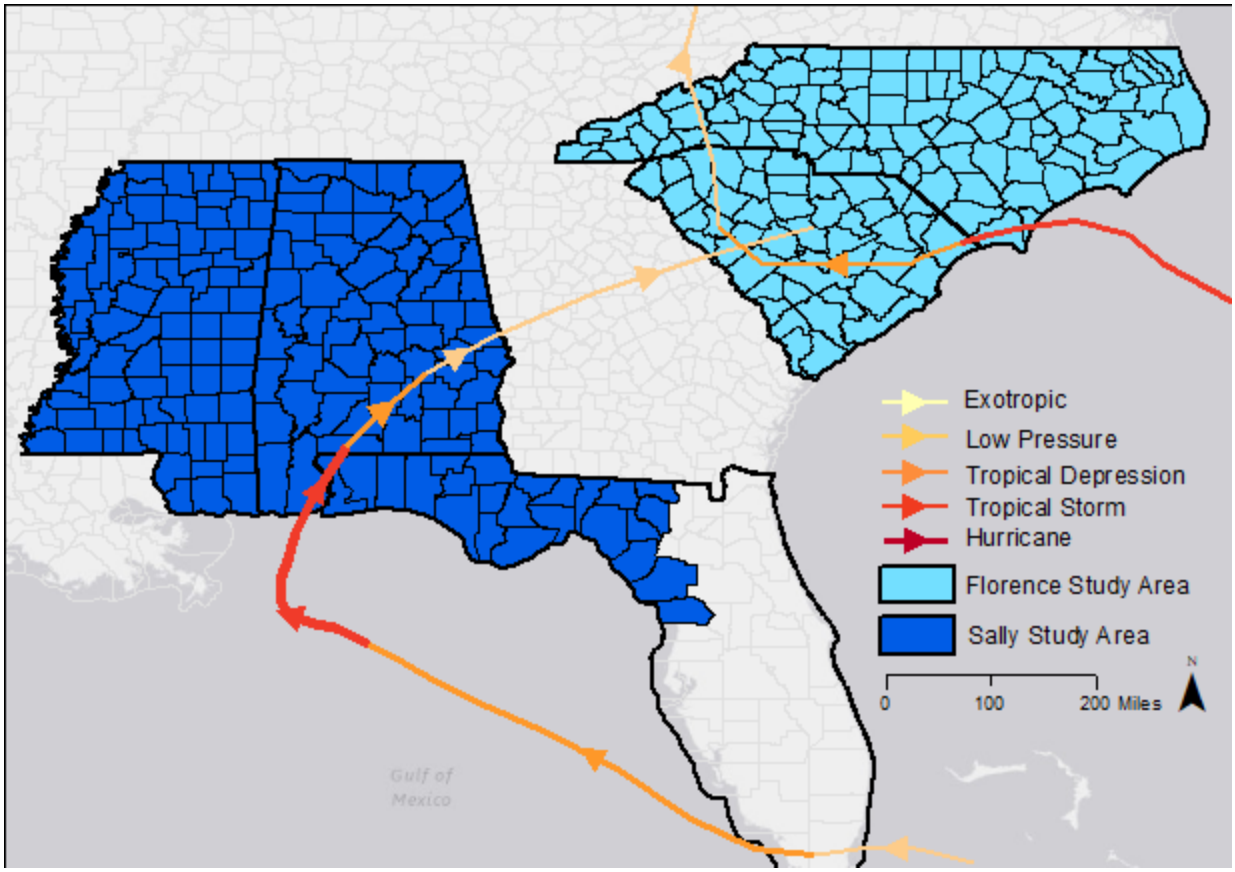


Figure 1. Study area. This map shows all of the counties that are included in the Florence (light blue) and Sally (dark blue) study areas.

Table 1. A summary of datasets used in this thesis.

Dataset	Source	Date	Application
EAGLE-I	DOE	2017–2020	Power Outages
American Community Survey	Census Bureau	2019	Socio-Economic Data
Topologically Integrated Geographic Encoding and Referencing (TIGER)	Census Bureau	2020	State and County Shapefiles
Urban-Rural Classification	National Center for Health Statistics	2020	Urban and Rural Land Classification
Disaster Declaration	Federal Emergency Management Agency	2017-2020	County Status
Tropical Cyclone Best Track	National Hurricane Center (NHC)	2018, 2020	Hurricane Track and Intensity

Table 2. A description of the datasets used in this thesis.

Explanatory Variable	Dataset	Description
Percent below poverty	American Community Survey	The percent of the population in a county below the poverty level in the past 12 months.
Percent African American	American Community Survey	The percent of the population that is African American.
Percent Minority	American Community Survey	The percent of the population that is not Caucasian or African American.
Urban-Rural Classification	National Center for Health Statistics	A six-level urban-rural classification scheme for US counties. These counties range from counties that contain large urban metropolitan areas to rural nonmetropolitan counties.
Disaster Declaration	Federal Emergency Management Agency	A binary variable consisting of Yes or No to determine if a county declared a disaster declaration.
Hurricane Category	National Hurricane Center (NHC)	Saffir-Simpson Hurricane Wind Scale classification of hurricane categories used as a proxy for hurricane wind speed.
Distance from TC Track	National Hurricane Center (NHC)	The distance from a county centroid to the closest point on the TC track that is used as a proxy for hurricane intensity.

CHAPTER 5: METHODS

The following methods were used across both Hurricane Florence and Hurricane Sally case studies.

5.1 EAGLE-I Data Preprocessing

EAGLE-I data containing all power outages that occurred from January 2014 to January 2021 were extracted from a SQL database to Comma-Separated Values (csv). This provided data from seven Atlantic hurricane seasons to analyze. I selected Hurricanes Florence (2018) and Sally (2020) for my case studies. I filtered EAGLE-I data from January 1, 2017 to January1, 2021 to capture all power outages that occurred during the 2018 and 2020 Atlantic hurricane seasons.

EAGLE-I collects power outage data every fifteen minutes for each county in the United States. In addition to the power outage count, FIPS codes along with the date/time of each outage are also recorded. There are 96 fifteen-minute pulling intervals per day. In other words, there are four fifteen-minute intervals per hour, and twenty-four hours per day. EAGLE-I only records data when power outages occur. Therefore, I manually added 0s to intervals with no reported power outages. This created a complete time series of county-level power outage data from January 1, 2017 through January 1, 2021. For each county in my study area, I aggregated the fifteen-minute power outage counts into daily averages by summing the 96 intervals and then dividing them by 24 hours.

5.2 Baseline Number of Daily Power Outages

In order to study the impact of hurricanes on power outage counts and recovery times, I first separated power outages due to tropical systems from ones likely caused by other means. I used the conventional annual Atlantic Hurricane Season of 1 June to 30 November. I first examined

the path of all Atlantic tropical storms that occurred from 2017 to 2020. I checked whether any tropical systems came within 250 nautical miles of either Hurricane Florence or Sally's location of landfall. I then referenced (Berg and Reinhart, 2021; Stewart and Berg, 2019) to determine if any past tropical systems impacted any counties within my study areas located on the United States East and Gulf coasts. For tropical systems that impacted my study area, I removed all power outages that occurred a week prior to a week after the system's closest point of intersection. This created a way to assess county-level daily power outages during the 2017–2020 Atlantic hurricane seasons without the influence of tropical weather. By averaging daily power outage counts for each county, I was able to determine the typical number of outages each county sees on non-hurricane days. I frequently refer to this value as "baseline" throughout my thesis. In other words, the baseline is the number of power outages typical for each county that is not caused by a tropical system.

5.3 Identifying Power Outages Due to Hurricane Florence or Sally

In the previous section, I identified daily county-level power outage counts not caused by TCs. I called this the baseline. Next, I subset the power outages that were the result of either Hurricane Florence or Sally in order to compare with the baseline. I first filtered all power outages that occurred between either hurricane's date of landfall through the first month post-landfall. I then calculated summary statistics for each county. Summary statistics included the minimum and maximum daily power outage count per county as well as the mean and standard deviation. I then created a new data frame that combined baseline values for each county along with the power outages that occurred during the first month after Hurricane Florence or Sally's landfall. I could then compare these two values (baseline and first month power outages), and filter out

days where power outages within the first month were higher than the baseline. This approach offered the first insight into power outages that directly resulted from either hurricane.

Next, I narrowed the time period to more accurately identify Florence or Sally-related power outages. NOAA base reflectivity radar and storm tracks helped me visualize each hurricane's path after landfall. It took both hurricanes approximately three days after landfall to move out of either study area. Based on these observations, I classified power outages that occurred within the first three days after landfall as ones caused by either Florence or Sally. A simplified workflow of this data processing can be seen in Figure 2 and Figure 3.

5.4 Analyzing Consecutive Power Outages

After identifying power outages assumed to have been caused by either Hurricane Florence or Sally, I then calculated the number of days in a row where these power outages were above the baseline. I refer to this as "consecutive power outages". The consecutive power outage count reset back to zero if reported power outages, thought to be caused by either hurricane, fell below the baseline. Damaged infrastructure from a hurricane can obstruct communication with the EAGLE-I observing system, which could result in superficially low power outage totals. This is a known limitation to using EAGLE-I data, which will be elaborated in the Discussion section.

I then identified the maximum number of consecutive power outages for each county. In other words, I found the maximum number of days in a row where power outages caused by either Hurricane Florence or Sally were greater than the baseline for each county. This produced the total number of days in a row without power where "Day 0" is hurricane landfall, "Day 1" is one day after landfall, and "Day X" is X days after landfall. Exploratory data analysis revealed a right-skew in the dependent variables *consecutive days above baseline*, *daily mean power*

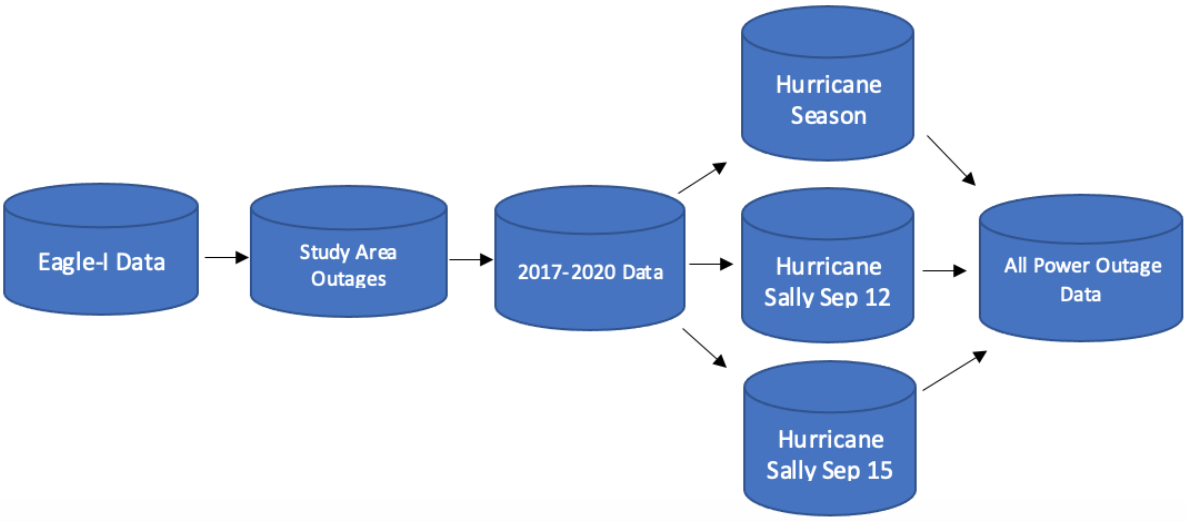


Figure 2. Power outage data processing. Power outage data are processed and filtered to create timeframes for each hurricane and hurricane season.

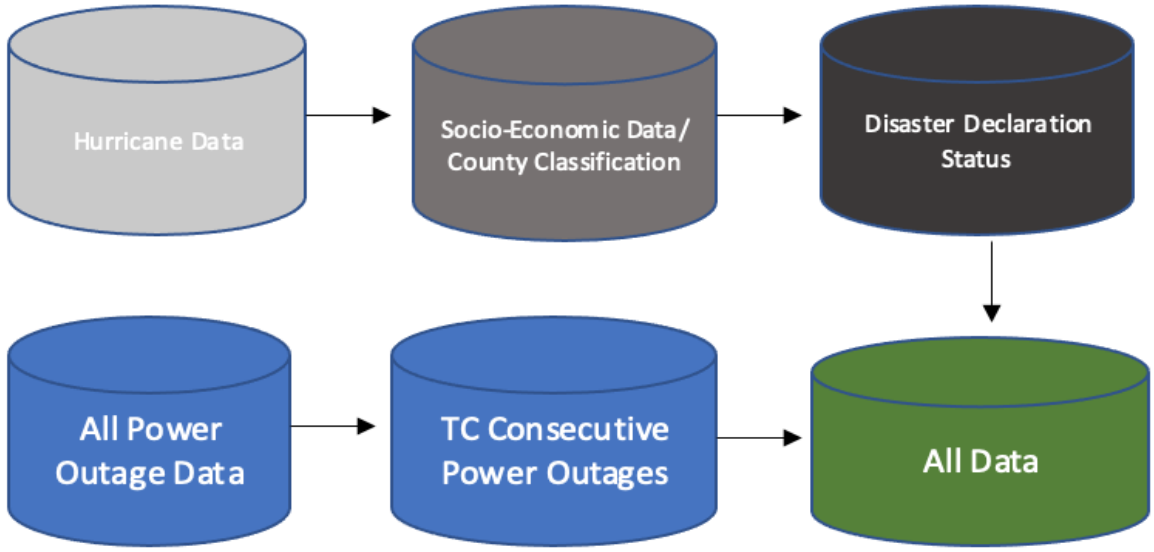


Figure 3. Data aggregation. Data from multiple sources are combined and filtered to only include the study areas.

outage, and daily maximum power outage for both study areas. This skew is used to inform which statistical methods are best suited for the data.

5.5 Factoring in Additional Variables that could Affect Power Outages

There are a number of additional variables that could affect power outage counts due to a hurricane. I explore a few examples here.

5.5.1 Effects of Socioeconomic Data on Power Outages

Since I am interested in researching relationships between power outage recovery time and socioeconomic status, I first used the TidyCensus package in R to collect ACS 2019 county-level socioeconomic data for each of the 117 counties across my Hurricane Florence and Sally study areas. I selected the variables *population*, *poverty status in the last twelve months*, and *race*. Data were normalized by county using the ACS population totals for each category. Black, African American and minority communities often lack economic and social resources when compared to their white counterparts (Chia-Chen Chen et al., 2007). For this reason, I focus my socioeconomic analysis on minority communities. I obtained the proportion of each county's population that identified neither as white or black by subtracting the proportion of population that is white and black from the total population. I refer to the proportion of each county's population that identifies neither as white or black as a *minority* variable. Individuals represented here may identify as Native Hawaiian or other Pacific Islander, American Indian or Asian, Alaska Native, Native Hawaiian or Other Pacific Islander (US Census Bureau).

I used a linear regression model to analyze the effect of *poverty status in the last twelve months, percent of the population that is Black or African American*, and *percent of*

the population that is a minority on the maximum number of power outages a county experiences during a TC, as well as the date at which the maximum number of power outages is reached. Because these variables could possibly be correlated with each other, I then tested it for multicollinearity using the built-in R function vif (Variance Inflation Factor). To determine which of these variables was the most influential, I standardized the regression coefficients of the linear model using lm.beta. Due to the strong right skew of the days counties were above baseline and the average daily power outage, Quasi-Poisson regression models were used to determine the combined influence of all of the variables listed above. A Quasi-Poisson model treats variance as a function of the mean and is used when analyzing over dispersed count data (Ma et al., 2014; Ver Hoef and Boveng, 2007).

When analyzing the consecutive days above baseline the top largest three anomalies were omitted from the data analysis. They corresponded with counties where the TCs made landfall and the damage was most severe.

5.5.2 Effect of Disaster Declaration Status on Power Outages

In addition to ACS data, I also analyzed county-level FEMA disaster declaration data. Disaster declaration data were first converted from Keyhole Markup Language (kml) to csv file format to work more easily with functions in R. I differentiated counties within my study area that issued disaster declarations versus ones that did not with a binary ("*yes*"/"*no*") variable. In order to determine if a county's disaster declaration status was associated with its consecutive power outage count, I performed a Quasi-Poisson regression for each study area.

To test whether counties within a disaster declaration took longer to recover from consecutive power outages, the following steps were performed for both TCs. I aggregated

counties by their disaster declaration status (*yes*/*no*). Next, I averaged the number of consecutive power outage days for counties in each category. When rounded to the nearest whole number, both hurricanes averaged two consecutive days of power outages. I chose two days as the threshold for determining whether a county quickly recovered from a power outage. For both hurricanes Sally and Florence, I plotted counties that recovered in two days or less and had issued a disaster declaration, and counties that took longer than two days to recover but did not issue a disaster declaration. This created a visual comparison (Figure 2 and Figure 3) of their spatial pattern to the post-landfall movement of their respective TC.

5.5.3 Effect of County Classification on Power Outages

Two analyses were conducted on both TC's study areas to determine if there was an effect of county urbanization on the rate of power outage recovery.

The National Center for Health Statistics' (NCHS) Urban-Rural Classification Scheme for Counties organizes counties into six categories. The categories are: 1 ("Large central metro"), 2 ("Large fringe metro"), 3 ("Medium metro"), 4 ("Small metro"), 5 ("Micropolitan"), and 6 ("Noncore"). To gain a better sense of the land use classifications within the data (proportion of urban versus rural land), I used a bar plot. I implemented the methodology used by Mitsova et al., (2018) to further reorganize the six classifications into two. The two new classifications were "urban" (county classification values 1 - 4) and "rural" (county classification values 5 - 6). I analyzed both classification schemes and used the nonparametric Kruskal-Wallis test to determine whether there was a significant difference between land use classifications and the days of consecutive power outages.

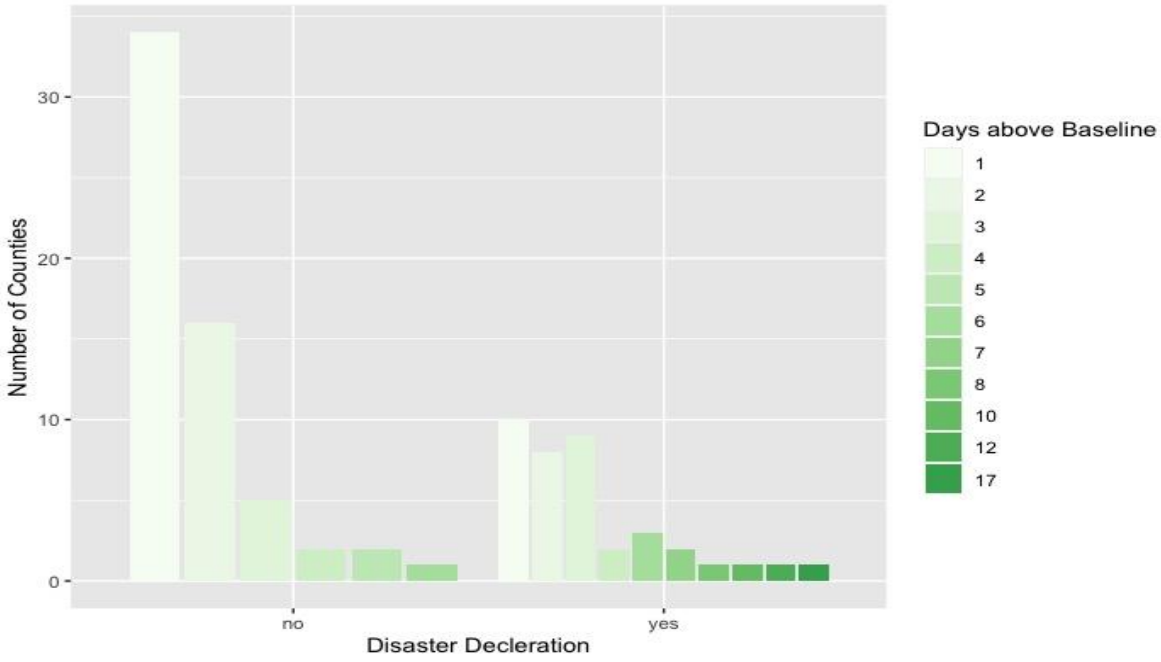


Figure 4. Disaster declaration status and time above baseline. This figure visualizes the disaster declaration status of counties impacted by hurricane Sally and the total days that they experienced above-average power outages.

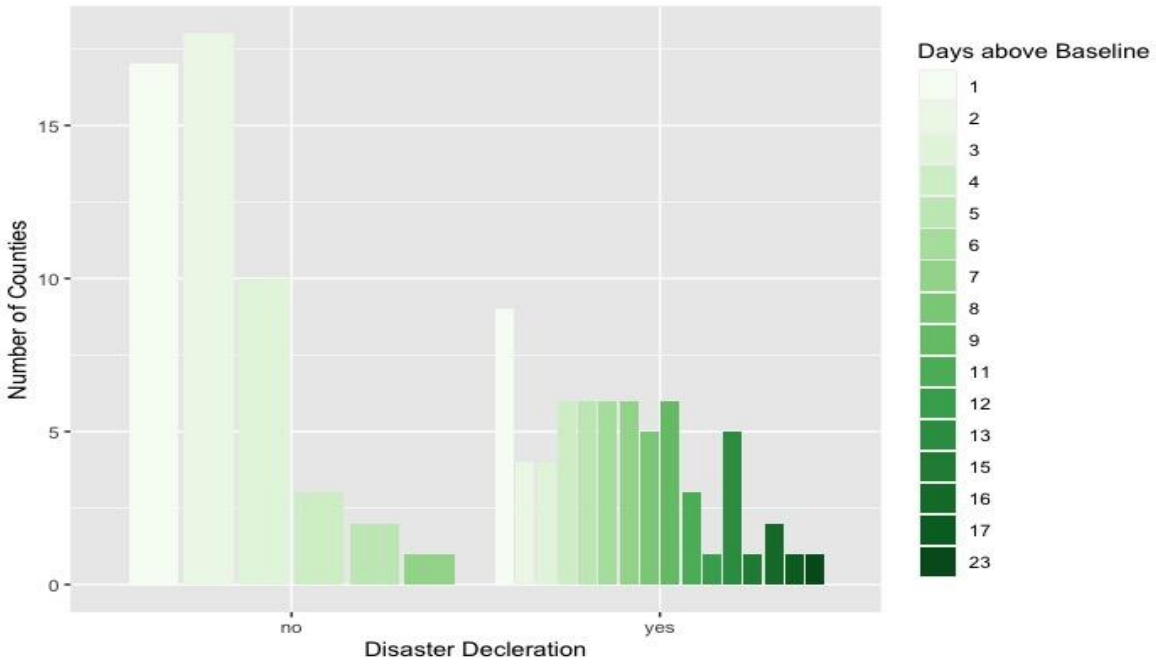


Figure 5. Disaster declaration status and time above baseline. This figure visualizes the disaster declaration status of counties impacted by hurricane Florence and the total days that they experienced above-average power outages.

5.5.4 Hurricane Intensity Metrics

I followed a workflow similar to that used in (Zhu et al., 2020) to calculate the closest distance between Florence and Sally's tracks to the counties in their study area. I obtained county centroids from the Census TIGER database and TC Best Tracks of Florence and Sally from the NHC. First, I extracted the centroids for every county in my study areas. Using the Simple Features for R package (SF), I transformed the tracks and centroids to the same spatial reference system. I then used SF to calculate the closest part of the TC tracks to the centroids in its study area. Once I had the closest section of the track to each county center (centroid), I calculated the distance between them, resulting in the nearest distance the TC came to a county's center.

The TC track data also contained attributes describing the stage of the hurricane's Storm Type: LO ("Tropical Low Pressure System"), TD ("Tropical Depression"), TS ("Tropical Storm"), HU ("Hurricane") and EX ("Extratropical"). These stages of TC development are characterized by varying levels of wind, highlighted in section 1.1, that contribute to the overall destructive potential of a TC (Elsner and Bossak, 2001). These categories were used as a variable to quantify the intensity of each TC at their closest point to county centroids.

5.6 Peak (Max) Power Outage

I performed the following methods to determine when the max power outages from Florence and Sally occurred in each county. This was done by selecting the date of the max power outage per county and then calculating the number of days away from the landfall it occurred where, "Day 0" is hurricane landfall, "Day 1" is one day after landfall, and "Day X" is X days after landfall. This process yields a "*days after landfall*" variable for each county. The count of counties and the day when the max power outage occurs can be seen in Figure 6 and Figure 7. These data

were then joined to the socioeconomic, land use classification, and disaster declaration data. The *days after landfall* value was then mapped, see Figure 8 and Figure 9, to determine if there was a spatial pattern in the data and a linear regression analysis was performed to determine if there was a significant relationship between the socioeconomics of the counties and the time of overall max outage.

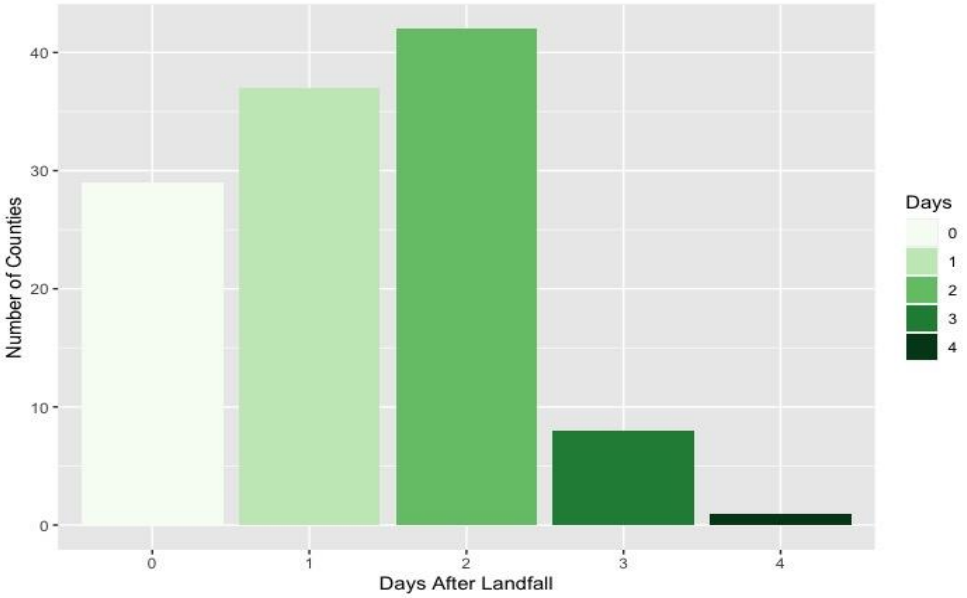


Figure 6. Days after Landfall (Florence) Distribution of days after landfall that counties experienced their highest number of power outages during Florence.

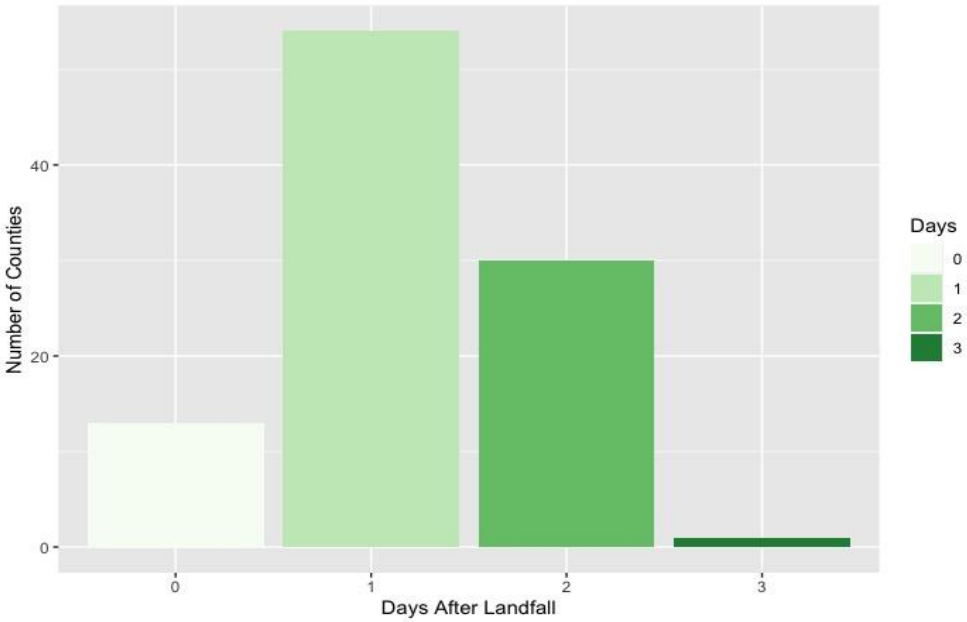


Figure 7. Days after Landfall (Sally) Distribution of days after landfall that counties experienced their highest number of power outages during Sally.

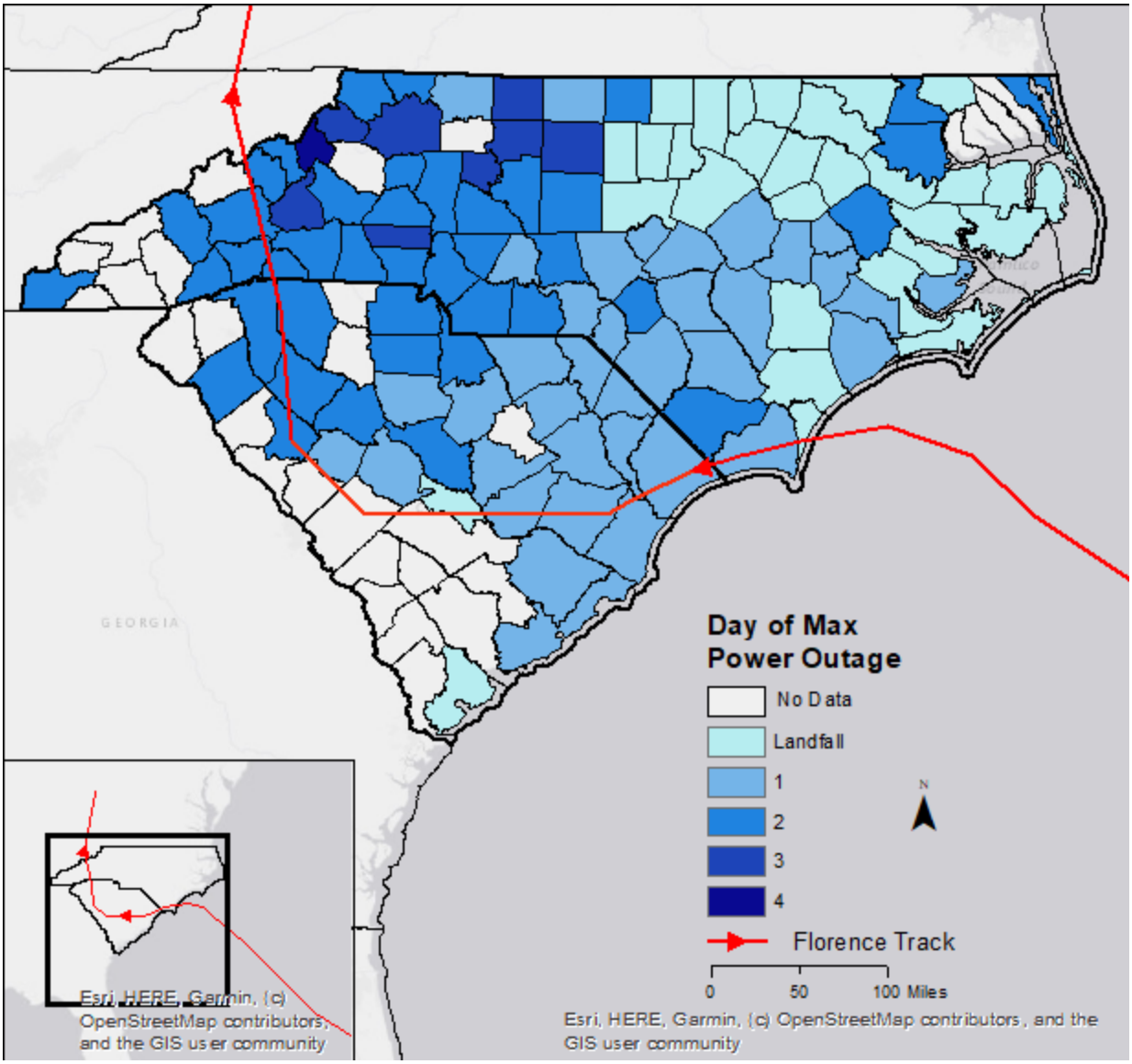


Figure 8. Days to max outage (Florence). Days after landfall that counties experienced their highest number of power outages during Florence.

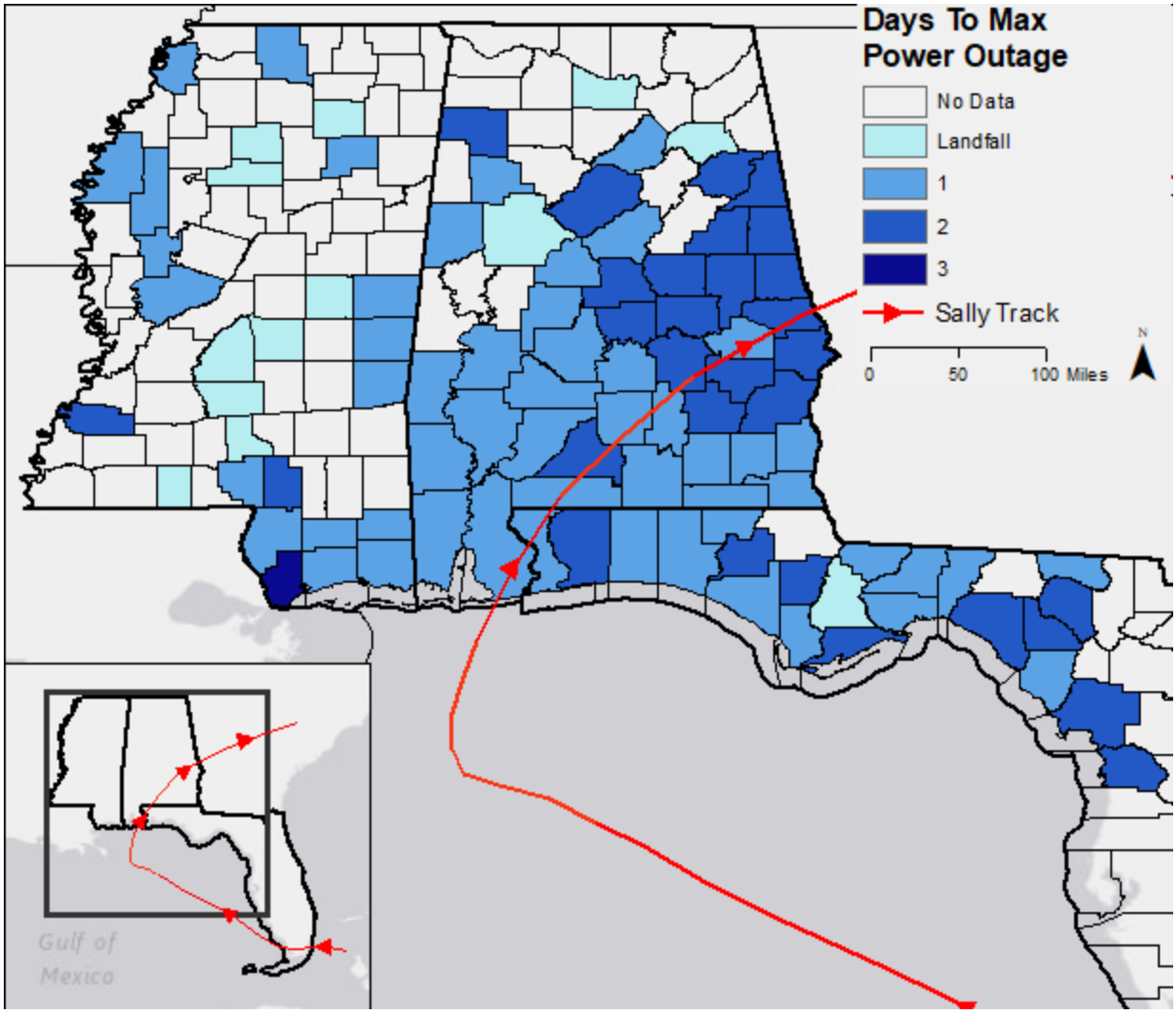


Figure 9. Days to max outage (Sally). Days after landfall that counties experienced their highest number of power outages during Sally.

CHAPTER 6: RESULTS

6.1 Florence and Sally Regression Analyses

Four response variables (*consecutive days above baseline, days until max power outage, max power outage,* and *mean daily power outage*) were modeled using Quasi-Poisson and linear regression across Florence and Sally's study areas.

6.1.1 Quasi-Poisson Regression Analysis

Results from the Quasi-Poisson regression analysis, found in Table 3 and Table 4, help explain power outage trends across the Florence and Sally study areas. The distance from either TC's path to the center of a county impacted was found to be statistically significant with an alpha of 0.05 for both analyses. This statistically significant relationship between a county's daily average power outage count and distance from the TC's path was found for both the daily average power outage and the number of days a county experienced power outages above baseline. For Florence, a statistically significant relationship exists between the number of consecutive days a county experiences power outages and TC strength as well as the percent of population below poverty. These two dependent variables (TC strength and percent of county population below poverty) also had a statistically significant relationship with daily average power outages. The regression results for Sally did not share as many similar significant relationships as Florence. A statistically significant relationship was found between the consecutive days a county experiences power outages above baseline and the percent of county population that is a minority. A statistically significant relationship between a county's daily average power outage count and storm type Tropical Depression.

Table 3: Quasi-Poisson regression results of counties' days above baseline during Florence and Sally.

Hurricane: Florence Coefficients:						Hurricane: Sally				
	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)	Sig
(Intercept)	1.70E+00	2.39E-01	7.116	1.37E-10	***	1.05E+00	2.64E-01	3.963	0.00015	***
Distance From TC Path	-2.66E-06	9.04E-07	-2.944	0.00398	**	-4.12E-06	5.54E-07	-7.447	6.15E-11	***
Tropical Depression	-1.19E+00	1.95E-01	-6.112	1.66E-08	***	-1.74E-01	1.53E-01	-1.139	0.25793	
Tropical Storm	-2.38E-01	1.48E-01	-1.613	0.10963		7.48E-02	1.31E-01	0.57	0.5704	
Percent African American	-1.56E-02	5.96E-03	-2.62	0.01009	*	6.52E-04	3.68E-03	0.177	0.8598	
Percent Minority	1.53E-02	8.41E-03	1.817	0.07211	.	4.96E-02	1.94E-02	2.558	0.01223	*
Percent Below Poverty	4.72E-02	1.69E-02	2.793	0.00621	**	6.02E-03	5.72E-02	0.105	0.91651	

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

Table 4. Quasi-Poisson regression results of counties' daily average power outages during Florence and Sally.

Hurricane: Florence Coefficients:						Hurricane: Sally				
	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)	Sig
(Intercept)	1.10E+01	4.57E-01	24.124	< 2e-16	***	7.56E+00	6.98E-01	10.834	< 2e-16	***
Distance From TC Path	-1.53E-05	2.16E-06	-7.079	1.44E-10	***	-9.44E-06	2.15E-06	-4.386	3.09E-05	***
Tropical Depression	-3.56E+00	5.32E-01	-6.694	9.52E-10	***	-9.43E-01	4.05E-01	-2.329	0.0221	*
Tropical Storm	-3.04E+00	5.70E-01	-5.329	5.30E-07	***	-5.85E-01	3.46E-01	-1.691	0.0943	.
Percent African American	-1.69E-02	1.93E-02	-0.876	0.383		9.66E-03	1.17E-02	0.825	0.4116	
Percent Minority	7.08E-02	2.91E-02	2.436	0.0165	*	-3.43E-02	6.23E-02	-0.551	0.5832	
Percent Below Poverty	-1.17E-01	5.38E-02	-2.183	0.0311	*	-3.25E-01	1.82E-01	-1.781	0.0782	.

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

6.1.2 Peak (Max) Power Outage Analysis Results

The counties impacted by hurricane Florence's right-front quadrant reached their maximum power outage during the day of landfall. The right-front quadrant of a hurricane is where the strongest winds and impacts are typically observed (Lonfat et al., 2004; Matyas, 2010). Maximum daily power outages, on the day of landfall, were not observed in the front-right quadrant in Hurricane Sally. The spatiotemporal distribution of max power outages for Florence and Sally can be seen in Figure 8 and Figure 9. The majority of max power outages attributed to Hurricane Sally occurred on the second and third day after landfall.

Results from the Quasi-Poisson regression analysis of max power outages a county experienced during Florence and Sally are found in Table 4. The percent of population below poverty, the hurricane's storm type and counties' distance from the hurricane track were all found to have a statistically significant relationship with the max power outage a county reached during both Florence and Sally. The variable percent of population below poverty was also found to have a statistically significant relationship, an alpha of 0.001, with the maximum power outage a county experienced during Florence. The linear regression model results for day after landfall of the max power outage during Florence or Sally, found in Table 5, showed no significant relationship with the percent of the population that was minority, African American or the percent of the population below poverty level. The only significant relationship shared between the two TCs in this analysis was with storm type *Tropical Storm*.

Table 5. Linear regression model results of the days it took counties to reach their max power outages during Florence and Sally.

Hurricane: Florence						Hurricane: Sally				
Coefficients:										
	Estimate	Std. Erro	t valu	Pr(>|t|)		Estimate	Std. Error	t valu	Pr(>|t|)	Sig
(Intercept)	3.70E+03	9.23E+02	4.006	0.000126	***	3.70E+03	9.23E+02	4.006	0.000126	
Distance Fro	-5.33E-03	1.71E-03	-3.114	0.002466	**	-5.33E-03	1.71E-03	-3.114	0.002466	***
Tropical Dep	-1.43E+03	5.33E+02	-2.681	0.008714	**	-1.43E+03	5.33E+02	-2.681	0.008714	**
Tropical Stor	-9.69E+02	4.60E+02	-2.106	0.037941	*	-9.69E+02	4.60E+02	-2.106	0.037941	**
Percent Afric	1.74E+01	1.34E+01	1.299	0.197245		1.74E+01	1.34E+01	1.299	0.197245	*
Percent Mino	5.65E+01	7.85E+01	0.72	0.473621		5.65E+01	7.85E+01	0.72	0.473621	
Percent Belo	-4.46E+02	2.04E+02	-2.19	0.031066	*	-4.46E+02	2.04E+02	-2.19	0.031066	*

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

Table 6. Linear regression model results of the maximum power outages a county experienced during Florence and Sally.

Hurricane: Florence						Hurricane: Sally				
Coefficients:										
	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)	Sig
(Intercept)	1.85E+00	1.76E+00	1.055	0.29384		2.14E+00	8.20E-01	2.616	0.01041	*
Distance From TC Path	2.85E-07	9.44E-07	0.302	0.76328		3.62E-01	1.77E-01	2.045	0.04374	*
Tropical Depression	1.52E+00	1.86E-01	8.181	5.39E-13	***	1.94E-01	1.54E-01	1.256	0.21223	
Tropical Storm	6.35E-01	1.73E-01	3.682	0.00036	***	-1.65E-06	5.72E-07	-2.879	0.00497	**
Percent African American	-5.16E-03	6.04E-03	-0.853	0.39545		-5.60E-03	4.35E-03	-1.287	0.2013	
Percent Minority	-3.84E-03	1.33E-02	-0.29	0.77251		-2.06E-02	2.65E-02	-0.778	0.43868	
Percent Below Poverty	-1.29E-02	1.90E-02	-0.678	0.49937		-3.05E-02	3.23E-02	-0.944	0.34755	

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

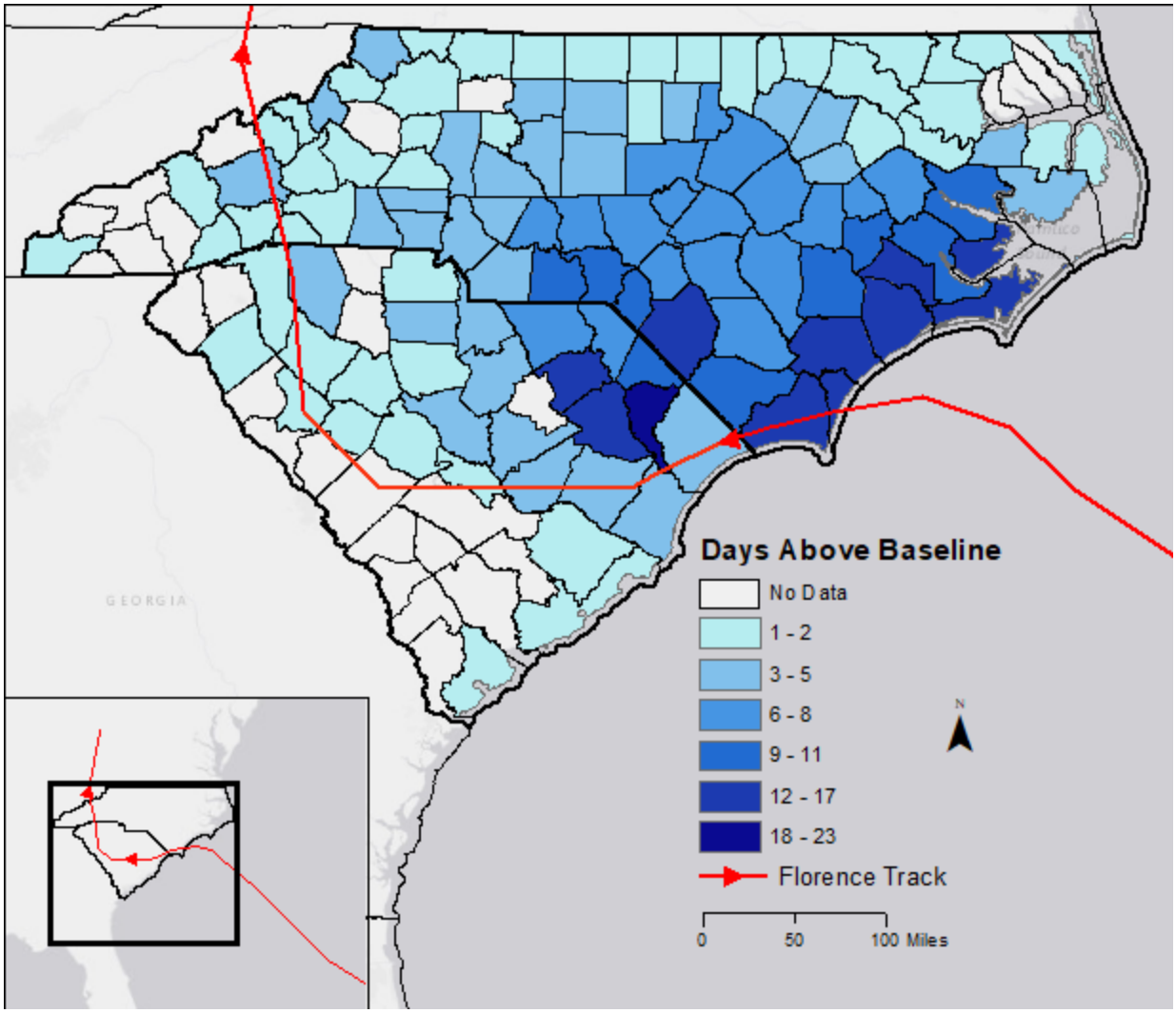


Figure 10. Days Above Baseline (Florence). The consecutive days in a row that counties affected by Florence experienced power outages above their baseline.

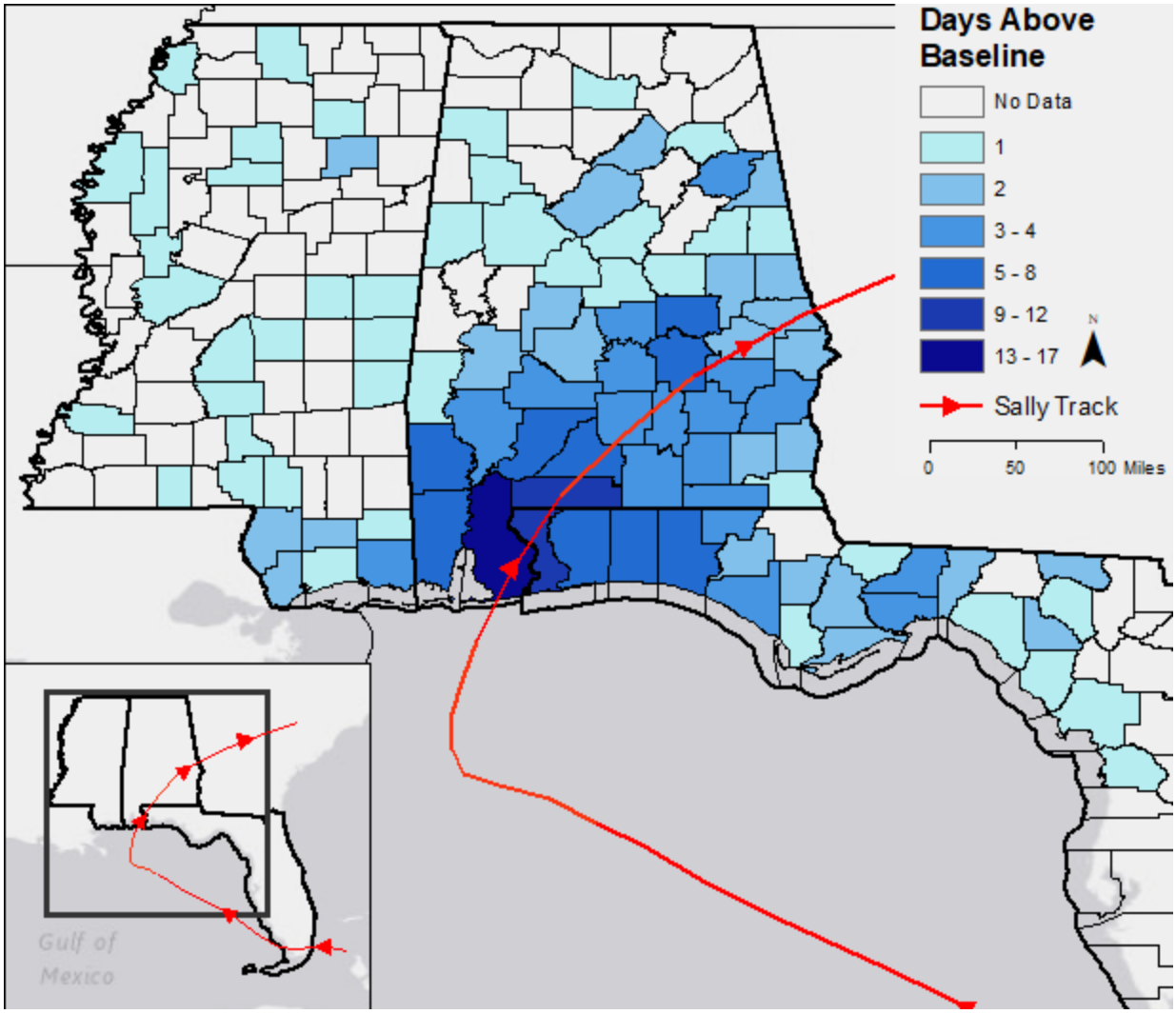


Figure 11. Figure 11. Days above baseline (Sally). The consecutive days in a row that counties affected by Sally experienced power outages above their baseline.

6.2 Disaster Declaration Analysis

I found several counties that were issued a disaster declaration had recovered faster than the average county recovery time of two days. While some counties that did not issue a disaster declaration took longer than two days to recover. I call these anomaly counties. One might expect that a county under a disaster declaration would suffer great impact from a TC, and therefore takelonger to recover than a county not within a disaster declaration. Or one might expect that a county that did not issue a disaster declaration would take longer than two days to recover because the county did not anticipate TC impact. This was not always the case, as some counties did not follow what I expected. These anomaly counties in both study areas are shown as having hatched lines in Figures 10 and 11. Dark blue hatched are counties that issued a disaster declaration and recovered to baseline within two days, and light blue hatched are counties that did not issue a disaster declaration and took longer than two days to recover. Anomaly counties that issued a disaster declaration, but recovered within two days were found along the periphery of affected counties or farther inland. Anomaly counties did not issue a disaster declaration but took longer than two days were found farther inland and either directly in Florence's path or to the right of it.

The Anomaly counties that had recovery times longer than two days during Sally, with the exception of two in Florida, were found inland along the path of the hurricane and along the right-front quadrant of the hurricane. Both study areas have counties that go against the assumption that all counties under disaster declarations take longer to recover. Instead, it suggests that counties further inland should consider issuing disaster declarations when hit by slower-moving, high-precipitation hurricanes.

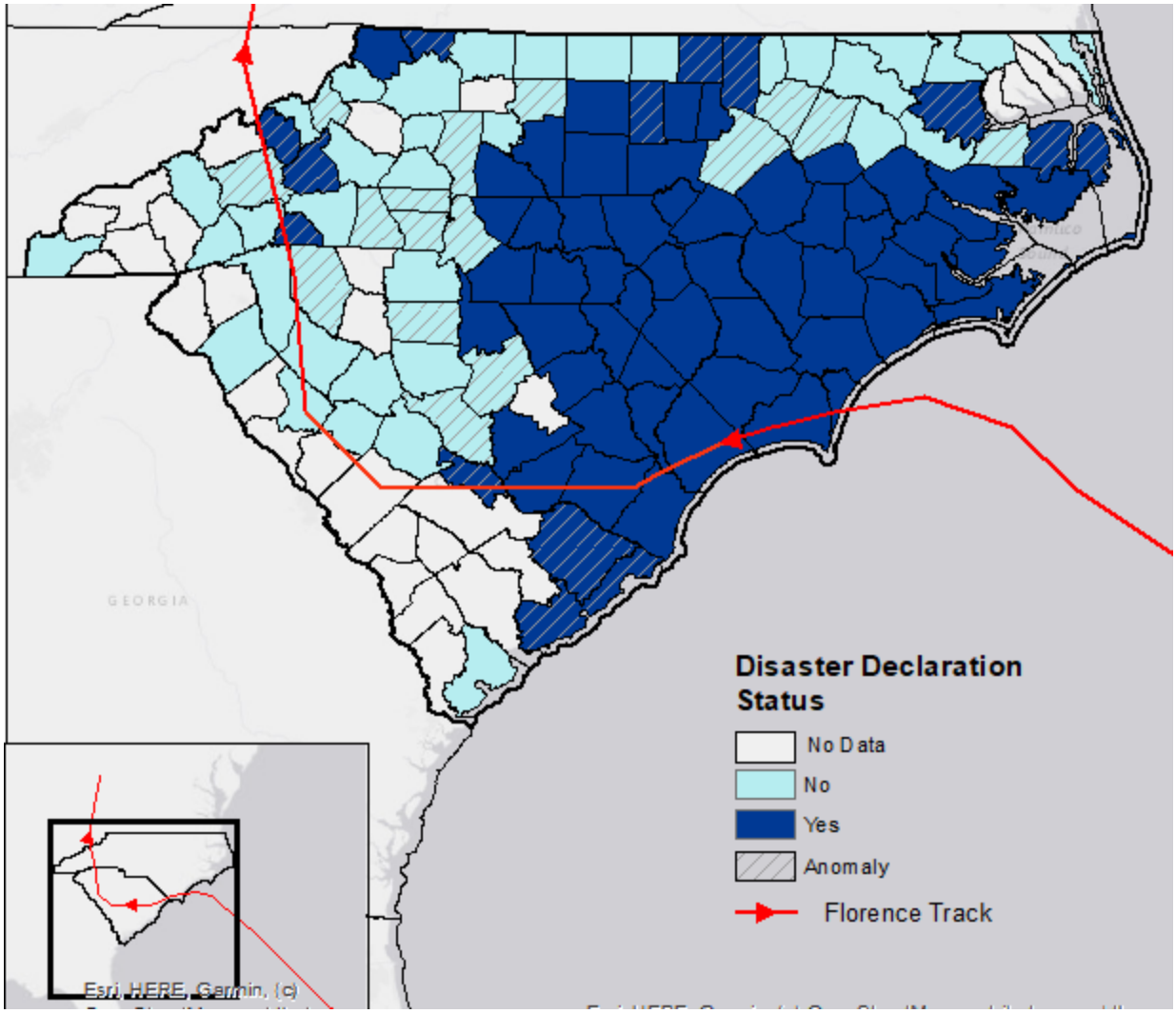


Figure 12. Disaster declaration status by county (Florence). Counties that recovered quicker (yes) or slower (no) than hypothesized are highlighted by diagonal hatched lines.

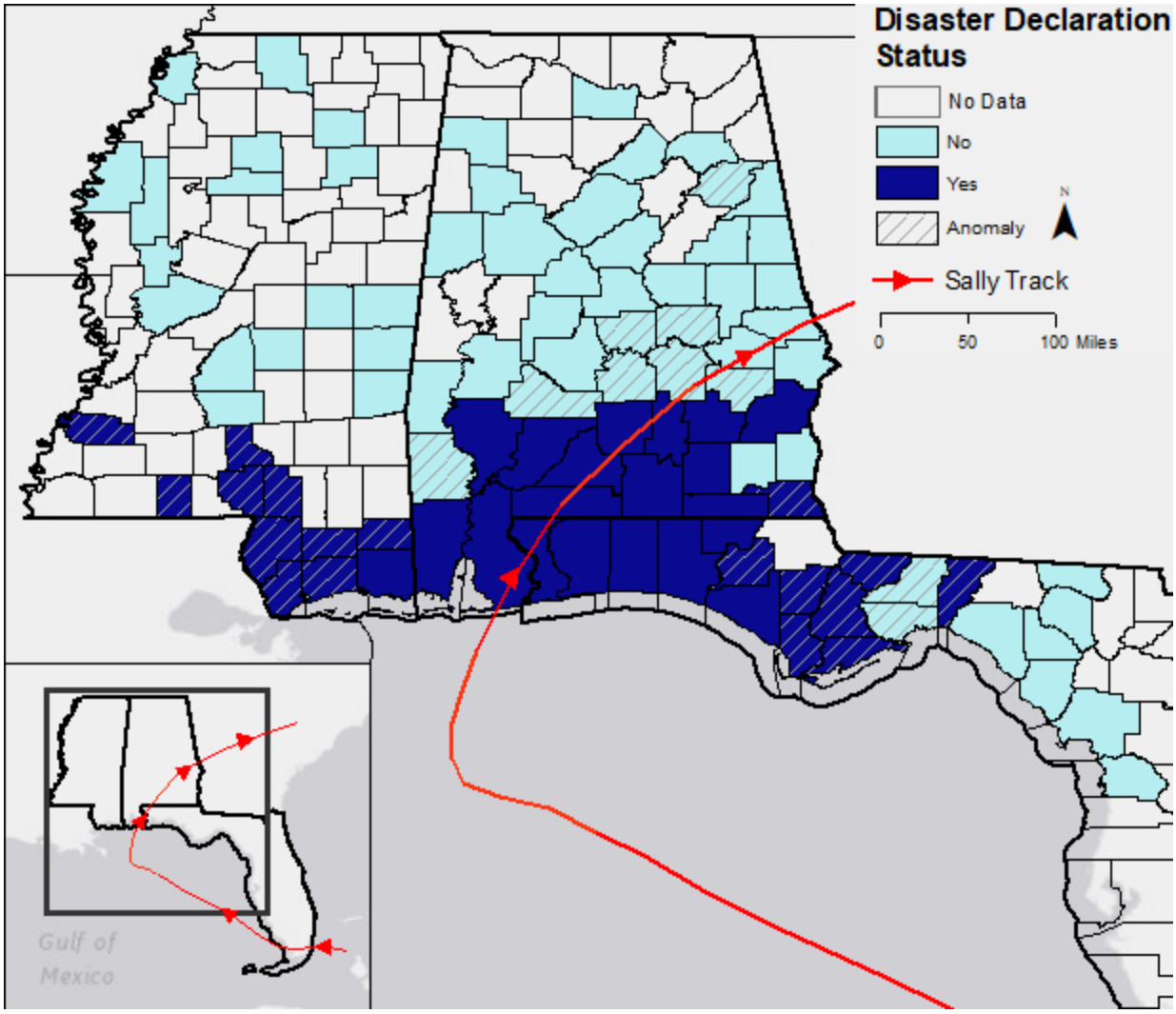


Figure 13. Disaster declaration status by county (Sally). Counties that recovered quicker (yes) or slower (no) than hypothesized are highlighted by diagonal hatched lines.

6.3 Rural and Urban County Classification Analysis

The analysis of rural and urban county classification was carried out in two parts, both classification schemes can be seen in Table 7. The first part was a grouped classification analysis, similar to the technique used by (Mitsova et al., 2018) and outlined in section 5.6.3. To determine if my data supports the findings in (Mitsova et al., 2018), I performed a Kruskal-Wallis test for both the grouped land classifications and the original 1-6 classification scheme. The results for the original classification scheme did not provide any statistically significant relationships with an alpha of 0.05 between county classification and response variables: consecutive days above baseline; daily mean power outage; time of max power outage; and daily maximum power outage. The re-classified data performed better for Sally, indicating statistically significant relationships between the variables and county classification. But for Florence, there were no statistically significant relationships. Because of this discrepancy between TCs, the county classification variable was excluded from the regression analyses.

Table 7. 2013 NCHS Urban–Rural Classification Scheme for Counties.

Urbanization Level	Description	Classification
1	Large Central Metro	Urban
2	Large Fringe Metro	Urban
3	Medium Metro	Urban
4	Small Metro	Urban
5	Micropolitan	Rural
6	Noncore	Rural

CHAPTER 7: DISCUSSION

In total, Hurricanes Florence and Sally caused over 1.6 million power outages (Berg and Reinhart, 2021; Castor, 2020; Miller and Blanks, 2020); (US Census Bureau, 2020b; US Department of Commerce, 2020). This work is important to better understand power outage trends, response, and recovery after a TC as well as the socioeconomic variables that may be at play. While I only examined two TCs, the methods can be used to examine future tropical systems.

7.1 Power Outage Recovery Variables

Statistically significant relationships between socioeconomic variables and power outage trends, recovery time, and restoration because resources are not equally distributed across communities. Minority communities are especially susceptible to the inequitable allocation of funds and assistance after a TC. Researchers, in multiple studies, conclude that it takes longer to restore power across lower income communities. (Duffey, 2019; Mitsova et al., 2018; Wilson, 1999). The regression results discussed further below corroborate these findings.

7.2 Power Outage Recovery Time and Daily Average Power Outages

7.2.1 Florence Study Area: Days Above Average

All variables except storm type *Tropical Storm* were shown to have at least a weak relationship with the consecutive days above baseline that a county experienced during Florence. So it is possible to infer that a county's socioeconomic status influences recovery time. Take Marion County, South Carolina, for example. Marion County is rural (a value of 6 in land classification) and has a population of 31,765 residents. It is located slightly inland within Florence's right-front

quadrant (Figure 8). Florence produced record breaking rainfall up to 19.56 inches of precipitation, which resulted in weeks of flooding (US Department of Commerce, 2020). According to the ACS data, 57% of the county's population is African American and 20% of the entire population is living below the poverty level. Of all the counties in the Florence study area, Marion took the most time to recover (Figure 8). The Quasi-Poisson regression results Table 2 support the time it took for this county to return to baseline, indicating poverty, percent of population that is African American and location in relation to Florence's track likely played a role in the county's power outage recovery time. Newspaper articles from towns within the county corroborate this hypothesis (Edwards, 2020). The Quasi-Poisson regression results for daily average power outage differed slightly, such that it suggested a statistically significant relationship with the percent of county population that is a minority and not with the percent of the population that is African American. It indicates that while African American communities might experience longer power outage durations, other minority communities might experience higher numbers of power outages.

7.2.2 Sally Study Area: Days above Average

The counties that took the most time to recover from Sandy were located near Sally's point of landfall and on either side of its track as it moved inland. Counties of note include Baldwin, Alabama and Escambia, Mississippi. Both locations saw severe flooding and over two feet of precipitation (R). Socioeconomic variables had more significant relationships across the study area for Florence than for Sally. The variable percent of population that is a minority was the only statistically significant socioeconomic variable for Sally. The regression model results (Table 3) for Florence indicated that there was a statistical significance for the percent of

population that is minority, but an alpha of .10 indicating that there might be a weak relationship across both study areas.

7.3 Disaster Declaration Discussion

7.3.1 Florence Study Area: Disaster Declaration

Figures 10 and 11 show counties that issued a disaster declaration and recovered to baseline within two days (Dark Blue with lines), and counties that did not issue a disaster declaration and took longer than two days to recover (light blue with lines). The areas that did not declare a disaster declaration and took longer to recover were located inland and along Florence's path except for four counties that were located along in the right-front quadrant of the hurricane. Florence's slow translation speed enabled it to break state precipitation records in both North and South Carolina, exceeding previous precipitation records by more than 10 inches (Stewart and Berg, 2019). This also resulted in record flooding across the interior of both states. Research attributes high-precipitation hurricanes with slow translational speed to climate change (Emanuel, 2021). It is widely reported that with a changing climate comes tropical systems capable of producing more precipitation. Just because a county is not directly located along the coast, does not mean the county will not be impacted by flooding and power outages. It is especially important for inland counties to understand hurricane risks and how evolving climate may impact them.

7.3.2 Sally Study Area: Disaster Declaration

Similar to the pattern found in TC Florence, the counties that took a longer time to recover from but did not have a disaster declaration were found inland along Sally's track. There were two counties (Figure 11) that did not follow this pattern, Wakulla and Leon. These counties were in the outer edge of the right-front quadrant and were impacted by a strong outer band of heavy rain, flooding and strong winds (Tallahassee). This further supports the reasoning for counties near the right-front quadrant of hurricanes

to prepare for extended periods of power outages. The counties that issued a disaster declaration but did not take longer than two days to recover were located along the edge of Sally's track.

7.4 Florence and Sally: Max Outages

Understanding when and where power outages occur during a TC is a vital step in allocating resources to recovery and ensuring that power is restored promptly. Power outages reached a maximum of two days after Florence's landfall, and then sharply decreased. Many counties (27/29) that reached maximum power outages on the day of Florence's landfall, were located in the right-front quadrant of the system's path (Figure 12). It is widely reported that a tropical system's most intense impacts are typically seen in the right-front quadrant. Damage from high storm surge, widespread flooding, and strong wind is commonly observed in communities located within this part of a hurricane. Counties with the most power outages on the second day after Florence's landfall were located directly in the system's path. This includes coastal counties directly leftward adjacent to Florence's point of landfall as well as counties further inland that the system passed. Having a better understanding of when counties are likely to experience their highest number of power outages can help utility companies and emergency planners mitigate damages and plan for better grid resiliency. This is especially true for counties that are further inland and have not historically had to deal with prolonged flooding. ***7.5 Limitations***

There are limitations in the data and analysis that must be addressed. EAGLE-I parses data from disparate sources across the internet, and thus relies on these sources to maintain the accuracy of their data. If the utility company or government data source that EAGLE-I obtains information from is inaccurate then this could lead to possible errors in the data and analysis. Infrastructure failures resulting in periods of missing data have occurred in the past, preventing EAGLE-I from

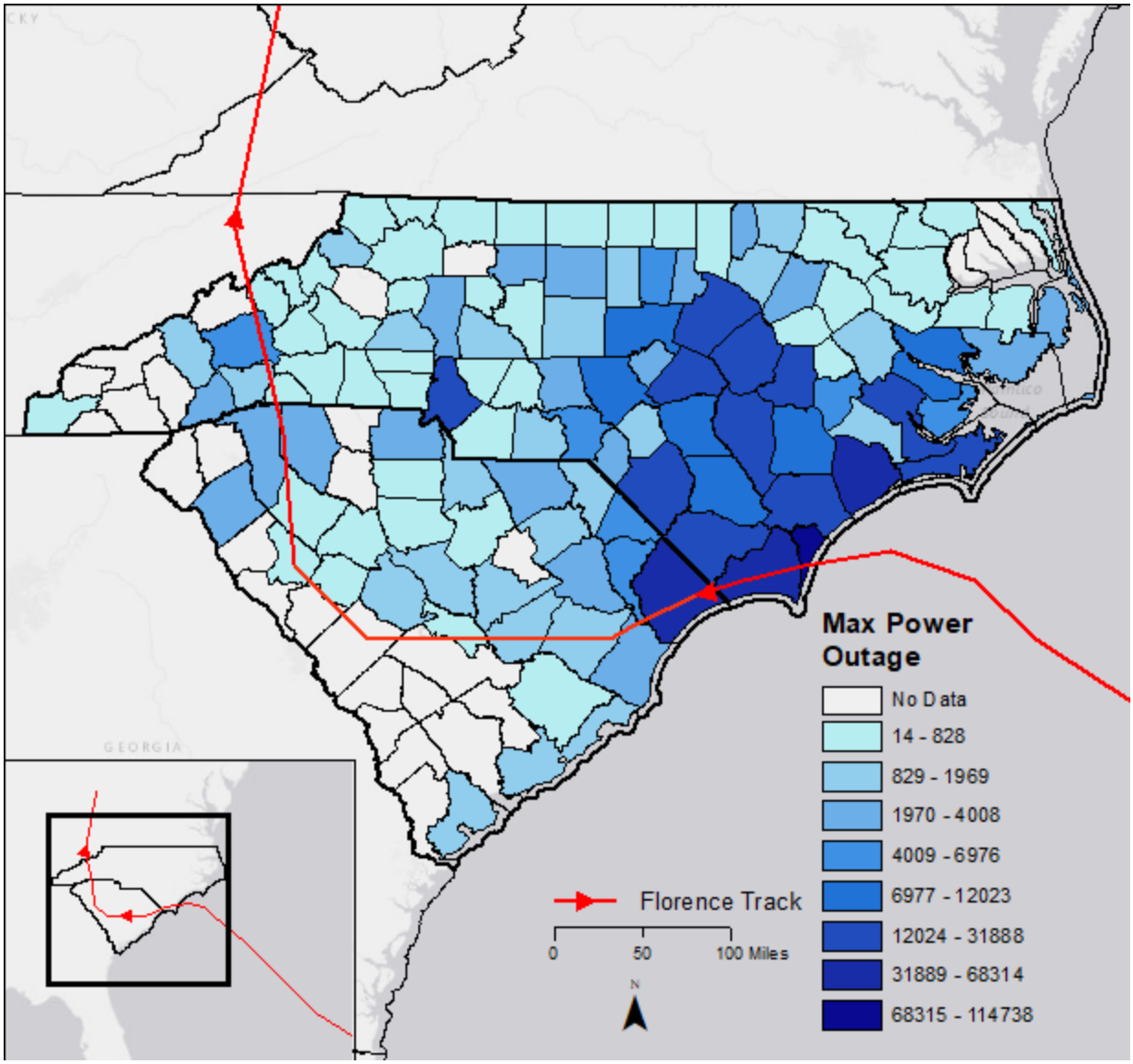


Figure 14. The Maximum Power Outage Count that Counties Experienced During Florence.

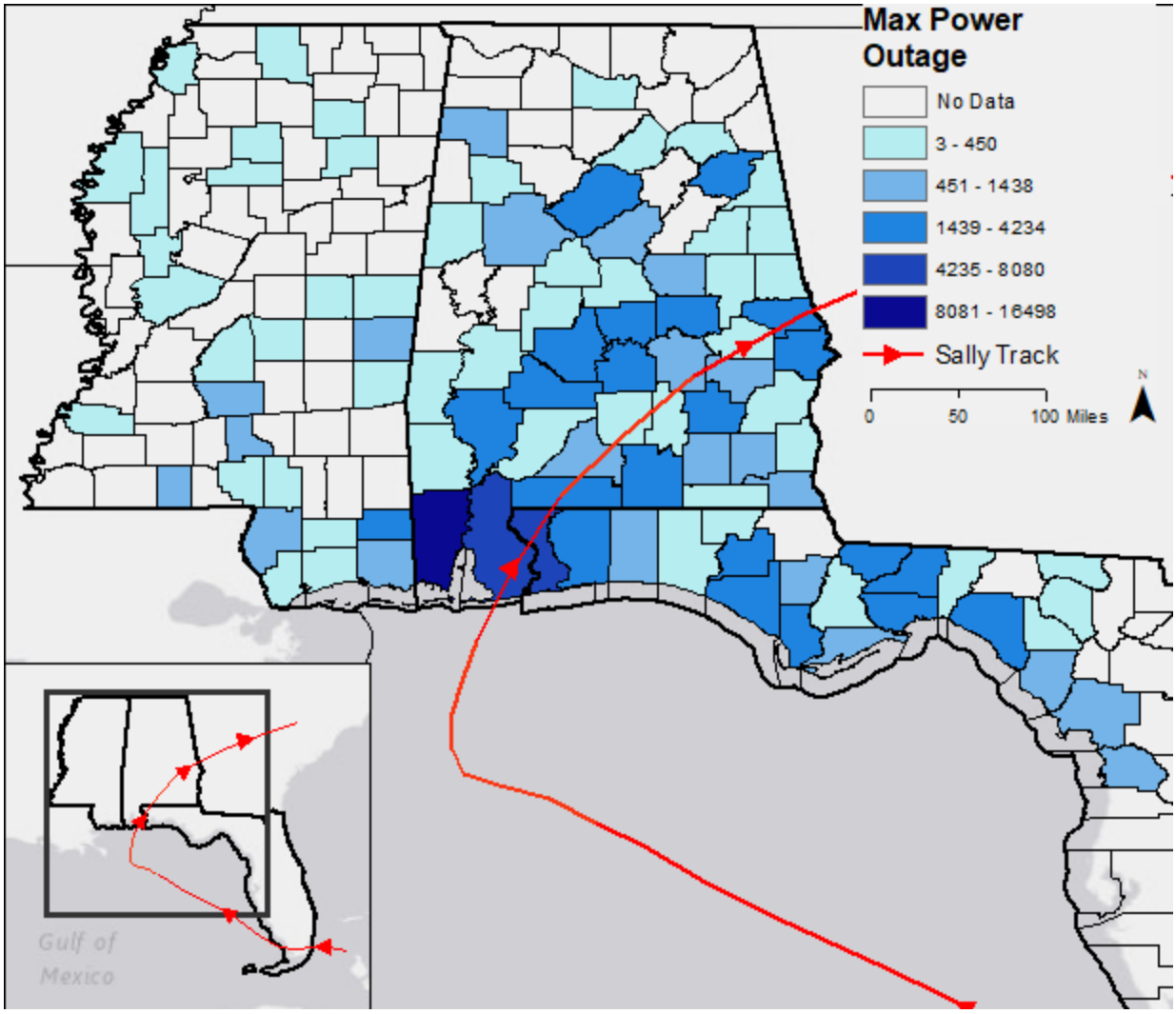


Figure 15. The maximum power outage count that counties experienced during Sally.

collecting data until the issue can be fixed. The data being analyzed was at county resolution, which possibly masks trends and relationships that are occurring at the sub-county level. The general age of infrastructure in a county was not taken into account. If a county's grid is better prepared for natural disasters, it is likely that the recovery rate and overall damage people experience will be lessened. I analyzed the EAGLE-I data at the daily level by creating a daily average power outage number, this could potentially prevent important trends in the data that are occurring on a higher resolution time scale from being observed. Power outage data from counties that did not experience an above *baseline* number of power outages were excluded from the data analysis. This was done in an attempt to only analyze areas that were experiencing power outages caused by the TCs affecting them. This could in turn produce selection bias, changing the outcome of the analysis.

7.6 Application and Extension of Research

As people continue to invest in coastal property, and coastal population density continues to increase, the potential impact of TC damage on communities rises exponentially. TCs threaten infrastructure, tourism, small businesses, local government, real estate, health care systems, and public transportation. Climate change, and the slower-moving high-precipitation TCs, will only continue to worsen the impact of future tropical weather on coastal communities. Recovery will likely not be equitable, as more affluent counties with greater access to resources will recover faster. Therefore, socioeconomic variables will likely continue to influence power outage recovery time for counties affected by TCs, as observed by my analysis.

In fact, understanding the impact of weather on communities is so important that in 2017 the United States Congress issued the Weather Research and Forecasting Innovation Act (Lucas,

2017). The “Weather Act,” as it is more commonly known, heavily involves research efforts conducted by NOAA. The NOAA Office of Oceanic and Atmospheric Research reports that the Weather Act sponsors 78 projects directly related to hurricanes (National Oceanic and Atmospheric Administration).

CHAPTER 8: CONCLUSION

8.1 Future Work

Florence's slow translation speed enabled it to break state precipitation records in both North and South Carolina, exceeding previous precipitation records by more than 10 inches (National Weather Service, 2019). This also resulted in record flooding across the interior of both states. Scientists attributed high-precipitation hurricanes with slow translational speed to climate change (Emanuel, 2021). Due to changing climate conditions, tropical systems capable of producing more precipitation are predicted to become more common. This will also change the way inland communities are impacted by flooding and power outages. It is especially important for inland counties to understand how to mitigate these risks and better prepare for future disasters. A potentially beneficial research question to build upon this thesis would be how inland flooding has affected power outages due to increased precipitation from hurricanes.

8.2 Summary

I used data collected by the DOE's EAGLE-I tool to research power outage trends, response, and recovery time due to two slow-moving, high-precipitation hurricanes. The first case study was Hurricane Florence, which made landfall as a Category 1 in North Carolina. The second case study was Hurricane Sally, which made landfall as a Category 2 in Alabama. I chose these systems as my case studies because they both share characteristics of hurricanes that are predicted to occur as a result of global climate change. In other words, Florence and Sally had slow translation speed and heavy precipitation. I identified a county's average number of power outages each day (their "baseline") using power outages recorded from 2017 through the 2020 North Atlantic Basin hurricane seasons (annually June through November). I calculated the

consecutive days after Florence and Sally made landfall that each county in the study areas exceeded this baseline and used this as the time it takes for the counties to recover from each TC. I analyzed the relationship between variables using Quasi-Poisson regression, linear regression, and Kruskal-Wallis tests. Results were inconsistent among the two case studies, however, locations of maximum power outages and the longest recovery times were generally within the hurricane's right-front quadrant and along the system's track. Analyses of the time a county experiences power outages above baseline, the daily average power outage and the max power outage experienced during hurricane Florence were found to be significantly impacted by the percent of population that is minority and the percent of the population that is below the poverty level. The only consistently significant independent variable across Sally's analysis was the affected county's distance from the TC track. In general, it was found that counties on the edges of both Florence and Sally that were issued a disaster declaration returned to baseline power outage levels faster than average. Counties that were further inland and within the right-front quadrant of the TC that were not issued a disaster declaration took longer than average to recover. The linear regression results for the time to max power outage for counties in both Florence and Sally did not indicate a strong relationship with any socioeconomic or storm type, except for storm type tropical storm.

Understanding power outage trends due to hurricanes is important for communities. Better prediction of when counties are likely to experience widespread power outages can help utility companies and emergency managers better prepare for future hurricane impacts. Utilities and emergency responders would have a better sense of where to deploy technicians, and if assistance is needed from neighboring states. Examples of resources included knowing where to open shelters or electronic charging stations as well as where to prioritize distributions of food,

water, and supplies. Communities can also better plan for their hospital system. For example, if a hurricane is forecasted to impact certain counties, patients can be preemptively transferred to hospitals outside of the most at risk counties. Knowledge of counties more likely to see power outages can help communities assist the elderly and other people who have no way of evacuating.

TCs will continue to threaten coastlines, with even stronger impacts expected due to climate change and increasing coastal populations. It is up to communities to prepare and respond in the most efficient manner possible. It is equally important for communities to understand their risk, especially if they are located further inland and may not have experienced devastating TC damage before.

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