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GIS Analysis of Housing Delinquency After Repeated Flooding In Horry County, South Carolina

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GIS ANALYSIS OF HOUSING DELINQUENCY AFTER REPEATED FLOODING IN HORRY COUNTY, SOUTH CAROLINA

By

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ABSTRACT

How communities react and change after disaster has been well-studied in recent decades. Knowledge around time scales, spatial scales, and specific facets of the built environment, such as housing recovery, have all developed largely around the opportunities that disasters have provided in understanding societal functions. This research has given policy makers and institutions insights into shortcomings of disaster specific recoveries, but these shortcomings are generalized beyond the scope of the originally studied areas. This thesis adapts this body of knowledge to a GIS methodology to help localize understanding to the coastal South Carolina context of Horry County. This low-lying area is at the bottom of a large watershed stretching to Virginia and is the county with the fastest growing population in the state. This overlay of increased housing demand and population growth onto a landscape where water is a fact of life creates communities that are increasingly vulnerable to loss and long recoveries.

These methods use residential parcel data from 2013 to 2020 to understand how the housing landscape in Horry County has responded to the substantial flooding events of 2015, 2016, and 2018 using an indicator of tax delinquency. Tax delinquency is used to signal a disinvestment from a property owner, which feeds a cycle of neighborhood devaluation and tax base decline. Understanding what physical parameters and areas of the county are unevenly delinquent will allow for future analysis to uncover what social characteristics and human processes correlate heavily with this neighborhood change in Horry County. Beyond location, parameters of position in urban or rural areas, as well as position relative to the Special Flood Hazard Area assess categorical differences in potential for delinquency.

Results of GIS analysis and statistical proportion tests reveal a 2014 wave of delinquency that precedes any flood impacts and therefore points to institutional origins. Subsequent years display clear changes in the distribution of delinquency across the county with delinquency hotspots and clusters developing in areas known to be subject to flooding. Categorically, rural areas are more delinquent than urban areas, but flood prone areas undergo a strong change from being significantly less delinquent than non-flood prone parcels to becoming significantly more delinquent as the county becomes more familiar with repeated flood loss.

Most of these results are consistent with current research, but also uncover unexpected intricacies present in Horry County, reaffirming the use in translating recovery literature findings to novel study areas.

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CHAPTER 1: INTRODUCTION

In any natural disaster, recovery is expensive and mired in uncertainty from the individual to community level. Housing recovery specifically is a critical component of total recovery at these varying scales and can account for 50% of the total recovery costs (Galindo et al., 2018). The housing market guides the recovery process in the United States, influencing the outcomes and character of afflicted communities along with it. The reliance on the market results in the ultimate vacancy or abandonment of some residential parcels which then act as a blight on the remaining properties, a spillover effect that decreases property values and therefore the status and buying power of the remaining homeowners (Zhang, 2012). This abandonment indicates a decline of community resources and prospects, perpetuating the cycles of abandonment and decline. Abandonment is not an evenly distributed phenomenon, and this result often depends on a multitude of factors such as damage, who owns the structure, and what resources are available for recovery (Peacock et al., 2014). Research, such as this thesis, seeks to assess and analyze society's interactions with the natural world through the lens of recovery after shocks. This thesis specifically builds knowledge that helps inform the recovery process of the relatively understudied Horry County, South Carolina, which was impacted by major flood events in 2015, 2016, and 2018. How the county's human landscape has been shaped by government institutions, a booming housing market, and a new surge of flood risk realization is understood through a parcel level analysis which isolates areas of the county which were statistically more delinquent during given years.

1.1 Purpose

This thesis serves as a modification of Zhang's (2012) analysis on Miami-Dade County post-Hurricane Andrew on housing vacancy. In that study multiple models of regression were employed to measure the impact of factors such as hazard-level, damage level, single-dimensional measures of social vulnerability, and density of vacant parcels on neighborhood vacancy rates. South Carolina is no stranger to tropical storms, and its position in the southeastern United States makes it particularly vulnerable to hurricane-induced coastal and riverine flooding. South Carolina has endured three Major Disaster Declarations (MDD) associated with tropical storms or heavy rains that granted federal assistance to the state for recovery since 2015 (Declared Disasters | FEMA.gov, 2021).

This thesis uses Horry County, South Carolina as a microcosm for examining the compounding effect of repeated flooding events on residential parcel vacancy in South Carolina. Social and physical data helps characterize the spatial patterns of abandonment at the census tract level of analysis. The period of record captures the three flooding MDD events (2015, 2016, 2018) and spatial analysis explores the temporal and geographic nature of what housing recovery patterns exist in Horry County as well as what locational characteristics correlate to those patterns. This analysis addresses both urban and rural communities and will assist South Carolina to conceptualize areas of potential community decline and change during the recovery from flood impacts.1.2 Research Questions and Hypotheses

Two research questions provide focus for this thesis. These include:

1. What was the spatial variation in housing vacancy prior to the 2015 floods?
2. How did the spatial pattern change during the period of record (2013-2020)?

Research question one will establish a baseline for how the county's residential delinquency behaves along classifications of urban, rural, flood prone, and non-flood prone, as well as how it is distributed spatially within the county's defined areal units (Census Tracts). This baseline will allow for longitudinal comparison of the annual datasets to years without the interference of any known flooding shocks in the period of interest. I expect that the urban areas will have lower delinquency rates given the increasing population pressure of people moving to the already densely developed coast of the county. I also hypothesize that those parcels with a higher expected flood risk will carry a higher delinquency rate given the environmental risks present.

With research question one providing a baseline, research question two will explore how delinquency in the county changed over the next five-year period. Given trends in the literature (Chapter 2), an increase in the rate of tax delinquency in the years following the floods of 2015, 2016, and 2018 is expected, followed by a decline in the rate of abandonment for the remainder of the record. This is informed by the understanding that events such as floods cause an immediate community shock followed by a return to pre-disaster levels as recovery progresses (Zhang, 2012; Peacock et al., 2014). I expect areas with relatively more abandoned parcels in the pre-event years will have steeper increases in the abandonment rate in the post-flood period. This would be consistent with the notion of the spillover effect that abandoned parcels can have in their community, where an abandoned parcel's impact on neighbor's home values increases the chances for nearby parcels to become vacant (Zhang, 2012).

If FEMA's 100-year flood plain accurately depicts increased levels of physical risk, then parcels in these Special Flood Hazard Areas (SFHAs) should experience more flooding impacts than those without, which may lead to higher delinquency in years following a flooding event. Drawing on studies on population changes following disaster, smaller communities lose a higher percentage of their population after disaster than larger communities, (Cross, 2014). As there is a paucity of literature on post-flooding housing abandonment in non-metropolitan areas, how the spatial pattern of delinquency for the entirety of Horry County will change is unclear.

Chapter 2 reviews literature related to broad disaster recovery, the timescales of recovery, system shocks, the organizational level of recovery, housing recovery, the housing landscape in the United States, and finally how community decline is understood through property vacancy. Although based in strong theoretical and empirical frameworks, there still exists gaps when considering how rural populations behave relative to urban counterparts, as well as how multiple cascading disasters impact the recovery process. Chapter 3 introduces the study area of Horry County, South Carolina, as well as explains the data and methods that are used to answer the two research questions posed earlier in this section. These methods use spatial and statistical analysis on annual datasets of parcels joined to tax delinquency data to measure how tax delinquency changed over the period of record. Chapter 4 explores the results of the analysis at both the whole-county and Census Tract level. Lastly, Chapter 5 contextualizes these results and discusses future research that can add value to the disaster recovery knowledge base and to recovery efforts in the future.

CHAPTER 2: LITERATURE REVIEW

The research questions of this thesis probe into how tax delinquency in Horry County changed over the course of 8 years, in which 3 years were related to major flooding. These questions build on current knowledge of recovery, housing, and community decline. As such, it is essential to understand these roots to adequately situate these empirical research questions within existing theory. This literature review starts with a foundation of disaster recovery's definition, scale, and associated social processes, before concentrating specifically on housing recovery. Why housing recovery is important individually and communally, how the housing market contributes to inequality, and how communities have restructured housing after disaster are explored. Finally, this literature reviews the processes associated with the lack of housing recovery, vacancy and abandonment. These processes have implications beyond a property's front door and have historically been associated both with community decline most greatly affecting socially vulnerable members of communities. These topics build on each other, and give an appropriate theoretical framing to the methods, discussion, and conclusions of this thesis.

2.1 Disaster Recovery

The term "natural disasters" serves as a trite misnomer, neglecting the role that society, political decisions, and diverse vulnerabilities play in creating a "disaster"

(Oliver-Smith, 2015). The disaster recovery field acknowledges the shortcoming of the word “natural” here, which in turn changes the focus from understanding the biophysical hazard to understanding what human processes coalesced to return the impacts that a disaster has, such as the social landscape as well as what resources are available to communities and individuals afterwards.

The very idea of recovery is somewhat contested as it is defined from fields ranging from sociology to engineering, all with unique measures and notions of what endpoint constitutes a recovery (Jordan and Javernick-Will, 2013). Studies that explore these intricacies largely examine the outfall from major events such as Hurricane Katrina or Hurricane Andrew at community and regional scales in order to extrapolate findings to other contexts and places (Zhang, 2012; Pais and Elliot, 2008; Peacock et al., 2014). These well-known events reveal uneven impacts, uneven recovery, diverse cultural response strategies, opportunistic redevelopment patterns, and disjointed federal programs, outcomes that can largely still be expected after major disaster events in the United States today (Arcaya et al., 2020; Galindo et al. 2018; Fussell et al., 2017; Raker, 2020). Recovery studies guide mitigation and recovery policies and programs to attenuate avoidable loss and suffering. Although some of the largest determinants of recovery are hazard exposure and damage level, these characteristics are emblematic of deeper social histories and landscape interactions (Cutter et al., 2014b).

There is significant research into the timescales of recovery, as it is a long-term process that does not have an exact conclusion. This compresses time for communities, sharply reducing the time needed to break the built and social environment and initiate what was previously only necessary in the long-term (Olshanksy et al., 2012). Research indicates that post-disaster timelines have four general periods of activity; emergency response, restoration, and two types of reconstruction (Kates et al., 2006). These are not discrete periods, but rather share temporal and functional overlap. Kates et al. (2006) indicate that each of these subsequent activity phases lasts about 10 times longer than the previous phase. Although not an exact number, this indicates that a 6-week emergency phase can result in a reconstruction period lasting 11.5 years from the initial impact, assuming there are no interruptions or other shocks. These phases do not happen in a temporal vacuum, as the various communities impacted represent systems already on trajectories in which the disaster acts as an exogenous shock (Lee, 2017). These shocks do not erase the historic trends of the community, but they are likely to increase or decrease the rate of change (Cutter et al., 2014a). As an example of how a storm can act as a shock to a system, residential vacancy in Miami-Dade County existed before Hurricane Andrew struck Florida's coast. The year after the storm had 20 times more vacant properties than the year before, and while this magnitude approached pre-event levels in subsequent years, it did not make a full recovery within the 8 remaining years of the study (Zhang, 2012).

An uneven recovery process can act as its own shock to the community, further magnifying the impacts of the disaster and hampering positive community change (Lee, 2017). Figure 2.1 displays the theoretical impacts that these shocks have on community trajectory. As a community is distorted through subsequent lenses of natural hazard impact or rehabilitation efforts, its trajectory diverges from what would be expected otherwise. The coastal counties of Mississippi that were affected by Hurricane Katrina which had a longer emergency period than New Orleans, were estimated to undergo a 19-

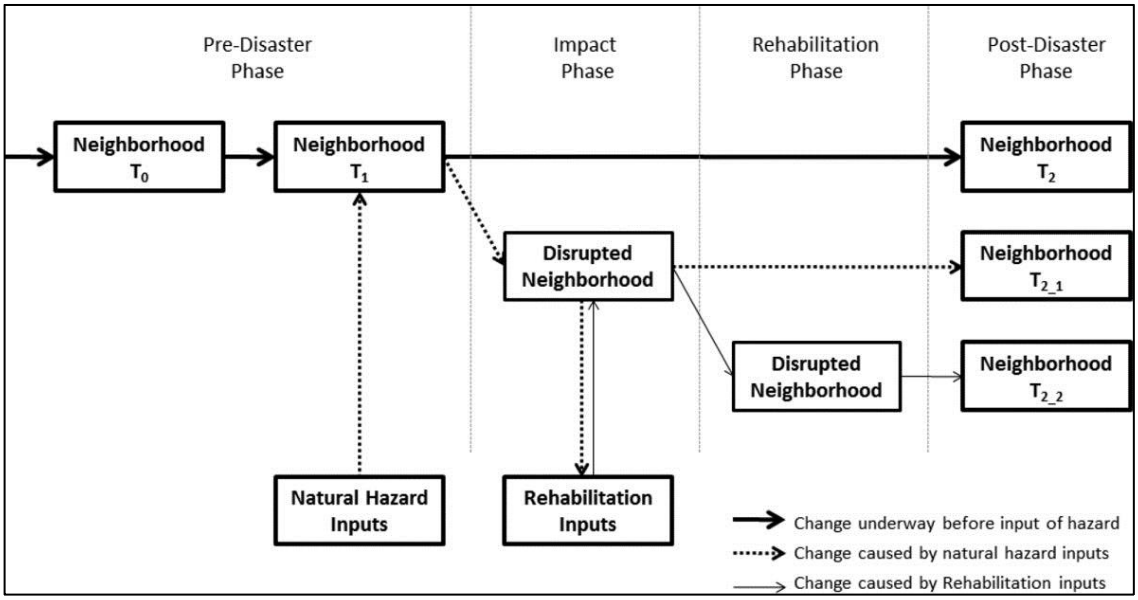

Figure 2.1: Community Trajectory Shifts (Lee, 2017, pg. 245)

year recovery process (Cutter et al., 2014a, pg.143). These estimates made based on a theoretical timeline could not account for the subprime mortgage crisis of 2008, the BP Deepwater Horizon oil spill in 2010, or Hurricane Isaac in 2012, all of which encumbered and altered the community's ability to move past a 2005 storm.

There is not much empirical work on these subsequent shocks, whether they be through uneven rehabilitation efforts or a true secondary exogenous disaster, but as disasters and their impacts become more frequent and expensive with a changing climate, the potential for cascading and intertwining impacts looms large (Cutter, 2018). Questions of how secondary or even tertiary hazards events impact community's trajectory remain largely conceptual but point to the potential for recovery fatigue and total place abandonment, implying communities may stop attempting to rebuild once their stress tolerance thresholds are passed.

The spatial scale of recovery, and at what scale recovery efforts should focus is an important research topic. In the case of the 1972 Buffalo Creek flood in West Virginia, aid was directed to individual entities, but the high level of destruction uprooted and broke apart the community because this aid strategy did little to keep the community relations intact (Erikson, 1976; Arcaya et al. 2020). For Buffalo Creek the sum (including community connections) was more than the parts (individuals). Without community connections intact, there was little chance for full individual recovery. Alternatively, in some events a catastrophe can catalyze a community's "resistant identity", whereby the individuals share a core experience and rally around it (Cox and Perry, 2011, pg. 402). In the case of wildfires erasing the place that existed before, residents found themselves pining for the forests that once surrounded their homes as they stood in the now-barren scenery. The erasure of what was familiar disoriented longtime residents who were placed back into new homes within a year (Cox and Perry, 2011). The nature of the community's response was the product of the event experienced, the preexisting landscape, the resultant landscape, the recovery processes, and the evolving community identity. All these factors interact to produce the psyche, comfort, and health of the residents and community.

The example of Buffalo Creek, nearly 50 years old, is mirrored in Katrina where disadvantaged communities faltered when their local social connections and capital were severed (Elliott et al., 2010). Here, social capital describes the norms and cultural institutions that foster communication, cooperation, and trust. This social capital is not practiced uniformly, and can be broken into multiple categories, bonding, bridging, and linking (Putnam, 2000; Hawkins and Maurer, 2010; Jerolleman, 2019). These categories were examined as Katrina impacted neighborhoods across Gulf Coast, spanning various socioeconomic settings and allowing for comparative analyses for how different groups utilize social capital during recovery. More-advantaged residents fell back onto "trans-local" and "bridging" social networks which may not be readily available to tap in the immediate aftermath, but through connecting to disperse social groups make it easier to recover while displaced, allowing for a quicker and more successful recovery at home. Similarly, advantaged groups had an easier time accessing "linking" social capital; the exchange of resources and information between individuals and institutions such as government agencies and aid organizations, especially along race and socioeconomic lines (Hawkins and Maurer, 2010). While all social groups used "bonding" capital, less-advantaged residents relied heavily on local "bonding" ties which are more useful in everyday life and immediately after a disaster but tend to falter when a disaster displaces those in the network. Without these insular networks intact individual recovery prospects suffer (Elliott et al., 2010; Hawkins and Maurer, 2010).

Directing aid and mitigation with an attention to utilizing social capital and enhancing community participation can shorten the recovery process and can help these networks survive the otherwise arduous and uncertain times after disaster, which in turn helps the individuals (Arcaya et al., 2020; Nakagawa and Shaw, 2004; Aldrich and Meyer, 2015). Without an intact community structure, individuals may resort to resettlement as the final attempt for recovery.

Recovery through resettlement is only understood through case studies and lacks a firm theoretical foothold, drawing inspiration vulnerability and migration theories, and sometimes neglects any clear theoretical back drop altogether (Greer et al., 2019). Methodologies are similarly scattered, extrapolating findings of individuals to entire communities and vice versa. Despite this, there is an understanding that this resettlement often occurs *in situ* as individuals move short distances in an effort to maintain their normal environment, but often inadvertently perpetuate the factors that enabled the initial destruction (Greer et al., 2019). Individual resettlement decisions engage in a calculus of environmental risk and social normativity, and in the case of Houston, Texas, the latter often dominates. For example, studies on post-buyout resettlement within Houston have indicated that when a buyout occurs in a Census Tract with a larger proportion of white residents, the affected household is likely to move a shorter distance and is likely to be closer to other bought-out neighbors (Loughran and Elliott, 2022). This individual decision making appears to be tied to attempting to maintain the pre-event racial status and social connections of the prior community, but at the same time ignores the environmental risks associated with the initial need to resettle.

Beyond differing scales, the focus of recovery research is often discipline specific, analyzing impacts on mental health, public health, business, demographics, or housing (Arcaya et al., 2020). Bolin (1985) argues that this last category, housing, is perhaps the most important single component of recovery for both the family and community scales (Comerio, 1998; Galindo et al., 2018).

2.2 Housing Recovery

Housing constitutes an integral part of the modern American Dream, and the structures associated with that dream constitute a massive portion of the building stock of any community (Comerio, 1998). This prevalence helps explain why housing recovery can account for over 50% of recovery costs from natural hazards (Galindo et al. 2018). Hence, patterns of housing recovery have garnered a fair amount of attention, especially in events where a large portion of an area's housing stock is damaged (Arcaya et al. 2020; Comerio, 1998; Peacock et al., 2014; Peacock et al., 2018, Zhang, 2012). In the media, disasters have been portrayed as spatially homogenous phenomena, affecting all those in their path equally, but housing recovery studies have revealed that this is an incorrect assumption (Zhang, 2012). Although recovery takes place after a disaster by necessity, the processes that constructed the landscape and built environment influence both the immediate impact and resultant recovery process (Quarantelli, 1995). The quality of construction and structure age have significant bearing over the amount of damage in disaster. Through housing "filtering", frequently those homes which are the most susceptible to damage are in neighborhoods with relatively high-minority and low-income populations (Peacock et al., 2018, pg. 576).

Filtering is a natural part of the housing market, which in large part guides housing recovery in the US, where those with less-buying power are constrained to cheaper structures and neighborhoods. This is a continuation from the more overtly racist practices of redlining neighborhoods, denying mortgages, and land use controls that confined minorities to these high-risk areas, and the outcomes from those practices are still evident in America today (Arcaya et al. 2020; Pendall, 2000). The housing market context has therefore condemned some people to greater structural damage from the onset of disaster, directly contrasting the narrative of homogenous impacts. In turn, Zhang's (2012) analysis on housing recovery in Miami-Dade County after Hurricane Andrew ties these increased damage levels with higher probabilities of property vacancy.

Just as the market guides the landscape before the disaster event, it is the dominant guiding force during the recovery process within the US, but there isn't consensus on how it operates (Peacock et al., 2014; Wyczalkowski, 2019). In New Orleans after Hurricane Katrina, Pais and Elliott (2008) found that New Orleans' recovery process focused on property damages and growth investments over supporting the most afflicted community members. The structure of this "recovery machine" shrunk rental opportunities, spiked rental rates for the remaining properties, and allowed those with preexisting capital and insurance to rebuild quickly and escalate their community status (Pais and Elliot, 2008). These market changes force the movement of the more vulnerable populations to new areas, and simultaneously invite new groups seeking to capitalize on reconstruction opportunities. These reactive changes construed a restructuring of communities into “recovery cores” and related rings that radiate outwards depending on their ability to find a foothold near the opportunities that the core provides (Pais and Elliot, 2008, pg. 1422). There is a competing theory constructed around the notion referred to as the “rent gap”, where developers and opportunists exploit damaged and low-value areas to turn a profit via redevelopment, which is supported by (Wyczalkowski, 2019). Both of these theories involve a restructuring of the community, either passively or actively encouraging the movement of low socioeconomic status residents. Which theory happens in actuality may be dependent on the disaster type as well as the impacted areas, but these findings are limited by the temporal and spatial resolution of demographic datasets.

Regardless of which theory prevails in specific scenarios, the ability to recover and prosper after disaster is tied to the ability to participate effectively in the market. This ability is tied to finances but correlates with groups understood to be more socially vulnerable. The ultimate result for affected populations who cannot effectively participate within the market are prone to greater instability. Studies on this residential instability (the frequency of changing residence) after disaster have found increased instability along gender, racial, and marital lines as the amount of event damage increases (Elliot and Howell, 2017). This matters because residential stability is tied to better health and well-being, and for that reason planners after Katrina recommended rebuilding with a diverse array of housing options, giving special attention to low and medium-income residents, increased funding from federal entities, and finally comprehensive local engagement in order to allow individuals a better chance participate in their local market.

(Olshansky, 2006). This is a prime example of academic research translating into policy and program recommendations.

2.3 Vacancy and Abandonment

Vacant and abandoned properties both signal the socioeconomic decline of a neighborhood and further contribute to that decline (Zhang, 2012). These properties are left this way because frequently owners do not want to invest capital in a deteriorated house, and instead use those resources to leave the property altogether. This newly vacated property makes neighboring properties less desirable for investment, which leads to further value leaving the area. As properties are vacated or abandoned, the taxes associated with the property no longer support the community's programs and plans, which leads to less for investments in infrastructure and public services. This is detrimental to the communities as much of planning relies on assumptions of growth, not shrinkage (Ehrenfeucht and Nelson, 2011). As the community's condition worsens, more properties become vacant, and the cycle continues.

Disasters can act as temporal shocks to this housing pattern as damages push properties past the point of no return in a shorter amount of time than without the disaster (Lee, 2017). The understanding of what specific spillover effects vacant and abandoned parcels have on their surroundings has been enhanced by modern GIS methods and data processing abilities that enable the analysis of decades worth of property specific data in a short amount of time. Zhang's (2012) methodology revealed that the closer Parcel A is to the nearest already existing vacant Parcel B, the higher probability that Parcel A will become vacant. In addition, increased durations of vacancy have progressively steeper influences on the devaluation of nearby properties (Newman et al., 2020).

It is important to state that vacancy is not the same as abandonment (Hillier et al., 2003). Vacancy points only to an occupational status of a home that can be short term, long term, or permanent. Abandonment denotes a series of attributes and processes that incorporates financial standing, physical condition, and functional ineptitude. With that distinction in mind, studies that hope to measure abandonment may have to settle for measuring vacancy because of data limitations. Studies that measure these qualities do so because they know what negative effects these properties can have on an area, but there is no universal way to capture these attributes in a dataset in earnest. This often makes it necessary to use proxy measures, which in turn necessitates specific and transparent definitions in methodology. Vacancy proxies present in the literature include property tax delinquency, metropolitan land use code records, and utility hook up status (Newman et al., 2020; Zhang, 2012; Galindo et al., 2018). All of these studies address single family properties, with little attention paid to duplexes and multifamily residences. Peacock et al. (2014) addresses the damage to these property types in terms of tax assessments and conclude that they are especially prone to disaster-induced change and slow recovery, but there is little additional information that can point to the relationship between disaster, recovery, and abandonment status of these properties.

In studies assessing vacancy as a measure of recovery and impact, there is often an attempt to explain local variations based on demographics, culture, or tenure. This level of analysis is performed so that more efficient targeting of recovery funding can be directed to those subpopulations that resulted in vacancy more frequently. Although the literature suggests there are overarching patterns of which subpopulations may struggle most with recovery, such a complex process necessitates place-based contexts (Peacock et al., 2014). For example, in joint analysis of Hurricane Andrew and Hurricane Ike, race was not a consistent indicator of recovery capacity, a variable which the literature often uses for explanation (Peacock et al. 2014; Zhang, 2012). Cultural differences and community ties can also act in the favor of some subpopulations that would have otherwise been thought to have low capacity for recovery, but it can be hard to predict how these interact before an event (Galindo et al., 2018). Consistently, tenure is an important indicator for the recovery of a structure and is one of the most commonly cited variables for vulnerability in housing recovery studies (Peacock et al., 2018; Lee and Van Zandt, 2019). Renting as opposed to owning carries correlations with more vulnerable populations, lower social activity in the community, and cheaper structures. Owners are also more likely to have access to resources such as insurance or loans to invest in repairs to their home, whereas renters have few rights, responsibilities, or resources relating to investing in the structure's recovery. This leads to higher rates of displacement for renters, and slower rates recovery for non-owner-occupied homes.

Although valuable insights, singular variables such as race or ownership can paint an overly simplistic picture of the local variables in an attempt to gauge local "social vulnerability" (Lee and Van Zandt, 2019). These narrow definitions of social vulnerability may be expanded by the research done in geography and hazards research to include a wider assessment of social components in an area. Although a fuzzy term used by many subfields, social vulnerability in a socio-economic is used to frame the range of subpopulations that may experience increased "potential for loss" (Mitchell, 1989). This social vulnerability interacts with the biophysical environment's vulnerability to result in a cumulative place vulnerability (Cutter, 1996). Within this context, social vulnerability is a multi-dimensional construct where variables are aggregated in a way to make sense of what sub-populations exist, and how vulnerable they are relative to each other. Research into how to calculate social vulnerability has spawned products such as the Social Vulnerability Index (SoVI®), which currently attempts to summarize 29 Census variables related to wealth, age, race, ethnicity, economic diversity, language, and housing composition and value (SoVI® Evolution, 2021). Products like SoVI® make it possible to compare populations across geographies, such as counties or census tracts, to explain uneven impacts and recovery more holistically. Although it is out of the scope of this thesis, an enhanced understanding of social vulnerability is essential to better understand the socioeconomic patterns that exist within a study area that join with measured processes such as tax delinquency.

2.4 Summary

This literature review has explored how uneven recovery can result in property abandonment and positively feedback into a cycle of further community decline. This understanding is informed by well-established research in disaster recovery, housing recovery dynamics, and how vacancy and abandonment impact communities. These impacts are not distributed equitably across socioeconomic classes with disparities along tenure, race, culture, and wealth divides. The uniqueness of place unfortunately makes it impossible to draw exact parallels from the study areas of the literature uniformly into new environments, especially when the literature so heavily analyzes urban communities. This thesis will contribute to this ever-expanding knowledge base with longitudinal analysis encompassing a full county in coastal South Carolina, as well as how multiple subsequent flooding shocks impacts property delinquency in the area.

CHAPTER 3: RESEARCH DESIGN

The research questions posed in section 1.2 are studied using all single-family residences in a full county in coastal South Carolina for the years 2013 to 2020. Property level locations were classified before being aggregated at the county level to allow for comparisons between classifications throughout the years of record through the use of proportion tests (Z-Testing). In order to measure where delinquency was changing at the "neighborhood" level, these points were also analyzed within their respective Census Tracts to calculate delinquency rates, changes in delinquency rates, and how those values are distributed across the county. This analysis is designed to isolate locational attributes (e.g. urban or rural) that show a relationship to increased delinquency over time, as well as portray how the spatial distribution of delinquency changed throughout years where the study area was impacted by major flooding.

3.1 Study Area

The study area is Horry County which experienced multiple major disaster declarations (MDDs) in recent years (2015, 2016, 2018). Horry County also has some of the most accessible GIS land record data in the region, which is why it was selected for analysis over neighboring counties. Differing GIS processes and tax delinquency record keeping make analysis across counties difficult, hence the selection of a single county. Horry is located in the Pee Dee Watershed and borders the Atlantic Coast to the

Southeast (Figure 3.1). The county is the penultimate stop for water flowing from areas extending far beyond its own borders, with a watershed stretching northwest all the way to Virginia. Water from North Carolina does not flow directly southeast into the ocean once reaching Horry County, but rather slaloms southwestward along the Intracoastal Waterway and Waccamaw River through a corridor of communities that have been affected in recent years. The Little Pee Dee River frames the western border of the county and then joins the Waccamaw near the southern corner of Horry County.

There are 15 Census Designated Places (CDP) in Horry County (Figure 3.2), many of which border the Atlantic Ocean such as Myrtle Beach, but there are also CDPs like Conway that are nested in between meandering swamps and channels further inland (US Census Bureau, 2020). The county only contains one Urban Area according to the 2010 Census Urban and Rural Classification (US Census Bureau, 2021). Tucked away from these population centers are rural populations situated on whatever usable land can be found. Including these areas in the analysis provides a unique opportunity to observe how rural housing recovered after disaster.

Horry County is prone to both coastal and riverine flooding events and received assistance via MDDs related to hurricanes or flooding three times in the last decade. These events produced $163.2 million (2019$) in property losses in Horry County alone (CEMHS, 2021). The federal government provided substantial support to aid in recovery as detailed below all values are in (2021$).

- The National Flood Insurance Program (NFIP) reports that in Horry County, from 2015-2020, there were building claims paid totaling $132.2 million (*FEMA NFIP Redacted Claims—V1*, 2021).

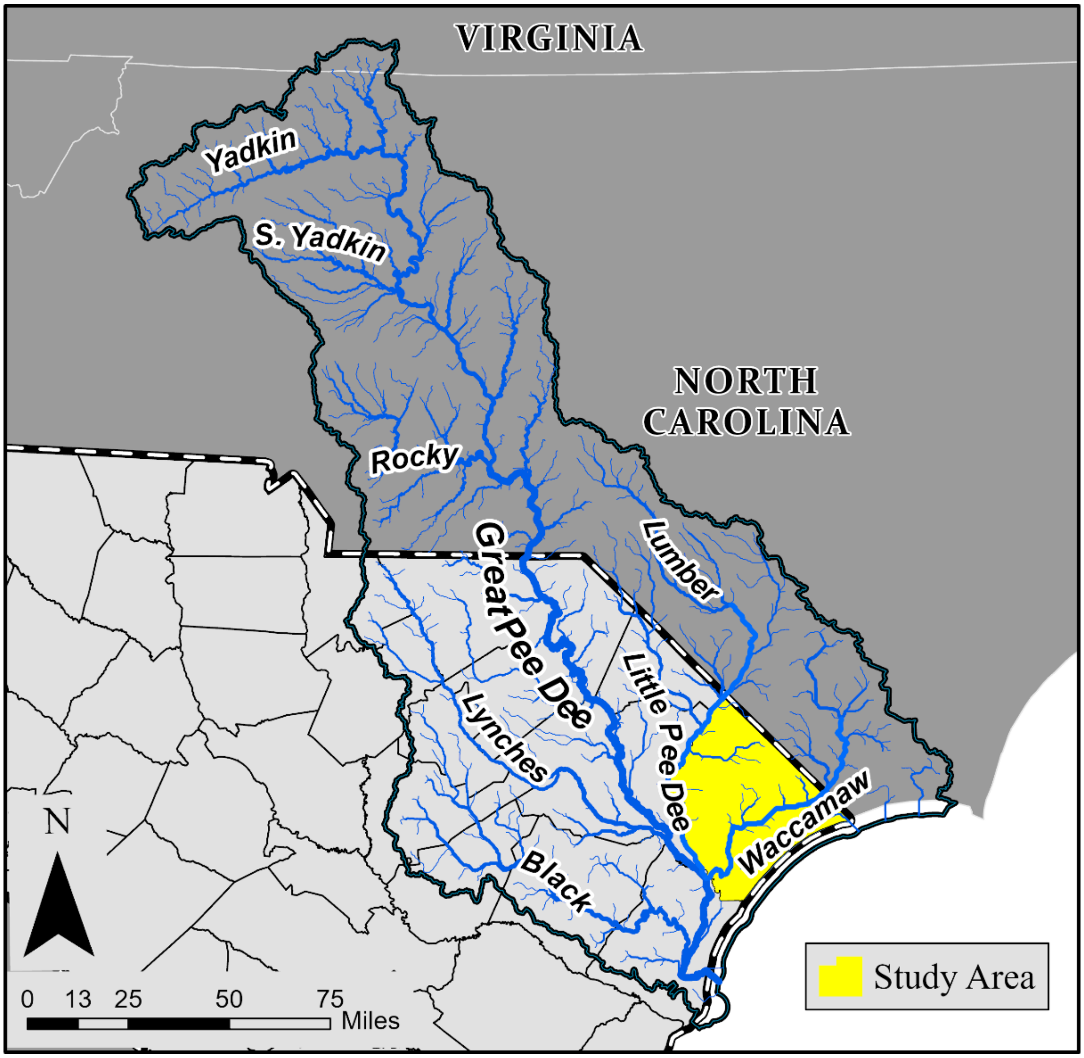

Figure 3.1: Pee Dee River Basin and Horry County Study Area

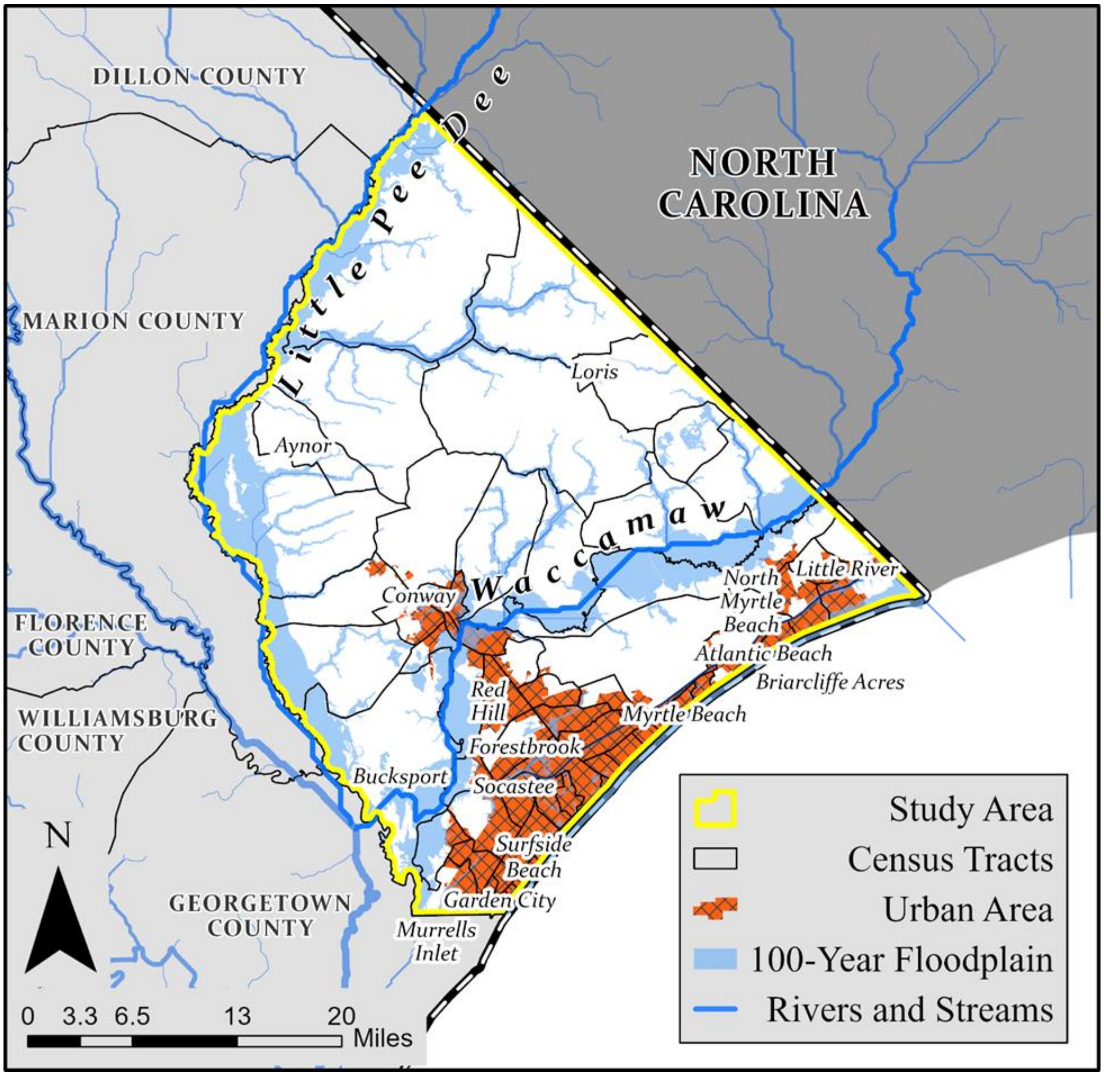

Figure 3.2: Horry County Detailed Study Area

- The Small Business Administration (SBA) provided $45.3 million to Horry County in Approved Total Loans from FY15 through FY20 (*SBA Disaster Loan Data*, 2021)
- FEMA has provided over $25.4 million in Individual Housing Assistance to homeowners and renters in Horry County in response to the disaster declarations related to the floods of 2015, 2016, and 2018 (*FEMA Housing Assistance Program Data – Owners - V2*, 2021)
- As of October, 2021, the South Carolina Office of Resilience (SCOR) has spent $6.2 million in Horry County to construct new homes with HUD's CDBG-DR funding allocated for the 2015 Floods. Projects for Hurricanes Matthew and Florence are ongoing (*Status of the Storm Recovery Efforts – South Carolina Disaster Recovery Office*, 2021).

As this thesis evaluates residential tax delinquency, it is essential to give context pertaining to the local housing market. Since 2012, the study area has been subject to increasing home prices matched with increasing demand. Any impact or recovery to the flooding events takes place within an environment where the average single-family homes are more valuable with every passing year. Figure 3.3 displays the single-family home data made available by the Coastal Carolinas Association of REALTORS, the realty association responsible for three counties including Horry, which is only available through 2011 (Crist, 2022). This is not enough time to capture the financial crisis of 2008, but the data does demonstrate the housing pressure that Horry operates under. The demand for housing has increased since 2012 with the expected increases in sales price and decrease in the number of days on the market. In a similar vein, Figure 3.4 displays

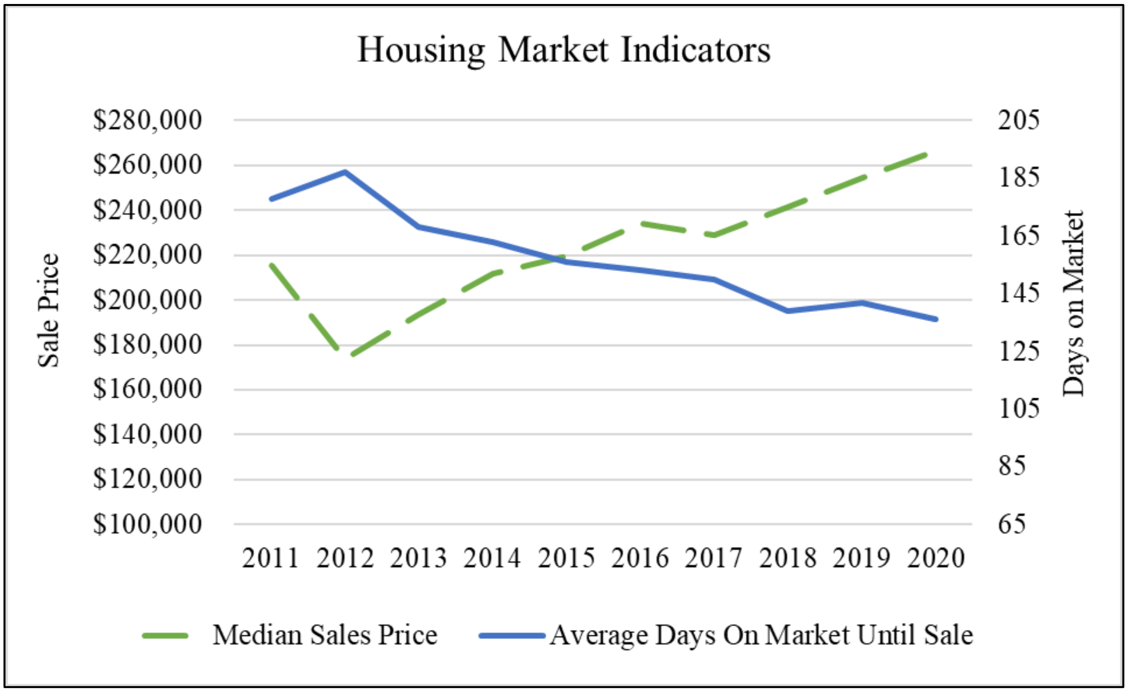

Figure 3.3: Housing Market Indicators for Single Family Homes in Horry County (Crist, 2022)

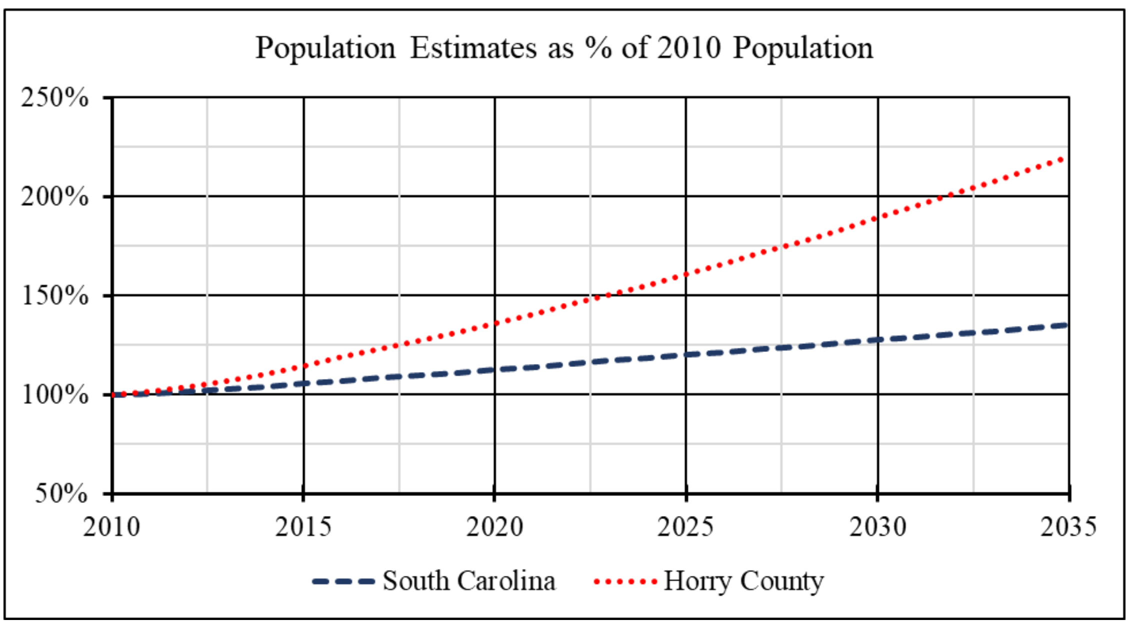

Figure 3.4: Population Estimates of Horry County 2010-2035 (Population Estimates by County 2010-2020, 2000-2009 | South Carolina Revenue and Fiscal Affairs Office, *2022)*

population estimates for Horry County compared to the entirety of South Carolina (*Population Estimates by County 2010-2020, 2000-2009 | South Carolina Revenue and Fiscal Affairs Office*, 2022). Between 2010 and 2015, the county had grown by 15%, a trend that far outpaces the rest of the state, and one that is expected to continue through 2035. This helps explain the burgeoning housing market in the area.

3.2 Data Sources

To follow the methodology outlined by Zhang (2012), this study uses a combination of spatial data (residential parcels) and sociodemographic data to assess the longitudinal nature of housing vacancy in Horry County. Parcel data was procured from the Horry County GIS Department for a period of time ranging from at least 2013 through the year 2021. The year 2013 is both 2 years before first event of concern (flooding in 2015), and also marks a change of the land use code schema that Horry County employs, making it a natural pick for a baseline year. Zhang (2012, pg. 1091) similarly captured parcels 2 years pre-event, but manages to track the data another 8 years post-event. Given the time that has elapsed between the 2015 and present day, the post-event record in this study is shorter.

Unlike Zhang's analysis, Horry's land use code is not sufficient to determine vacancy or abandonment. Therefore, it will be combined with annual tax delinquency data to indicate financial abandonment. Tax delinquency is an institutionally driven data point, as it is are dependent on local officials and the local bureaucratic processes. To be tax delinquent in Horry County begins a two-year process, which if not intervened upon, does ultimately result in foreclosure of the property. Property taxes are informed by property values which are reassessed on a five-year cycle, with the most recent three reassessments being held in 2019, 2014, and 2009 (L. Roscoe, personal communication, April 13th; *2019 Reassessment, 2022*). As this study is focused on housing recovery, only residential parcels will be considered in analysis. Horry County has 27 unique residential land use codes, and as of 2013, these categories were representative of over 212,000 parcels. To reduce the parcels considered in analysis to include only residences, this study only used parcels that had the land use code for single family homes (101) in 2013. This dataset contains 72,121 parcels.

3.3 Data Processing

To prepare the data for analysis, every year of Horry County's parcel layers were queried to include only land use code 101 which designates "Residential 1 Family" parcels. The remaining parcel polygons were converted to point format representing the centroid of the parcel. This was done to simplify the geoprocessing procedures by both saving computer processing time as well as allowing for uniform binary classifications of whether a parcel was considered urban or in the floodplain.

These points, one file for each year of data available, were then joined to Horry County's delinquency data for the appropriate year via a shared Parcel ID. The resultant table indicated with a 3 or 5 that the parcel was tax delinquent for that year. This value was turned into a binary delinquency attribute. The generalized locations of these delinquent parcels is shown in Figure 3.5, which displays the widespread nature of delinquency across the county in 2013. Each parcel point was then spatially joined to the FEMA 100-year floodplain, which was comprised of flood zone A, AE, and VE. If the

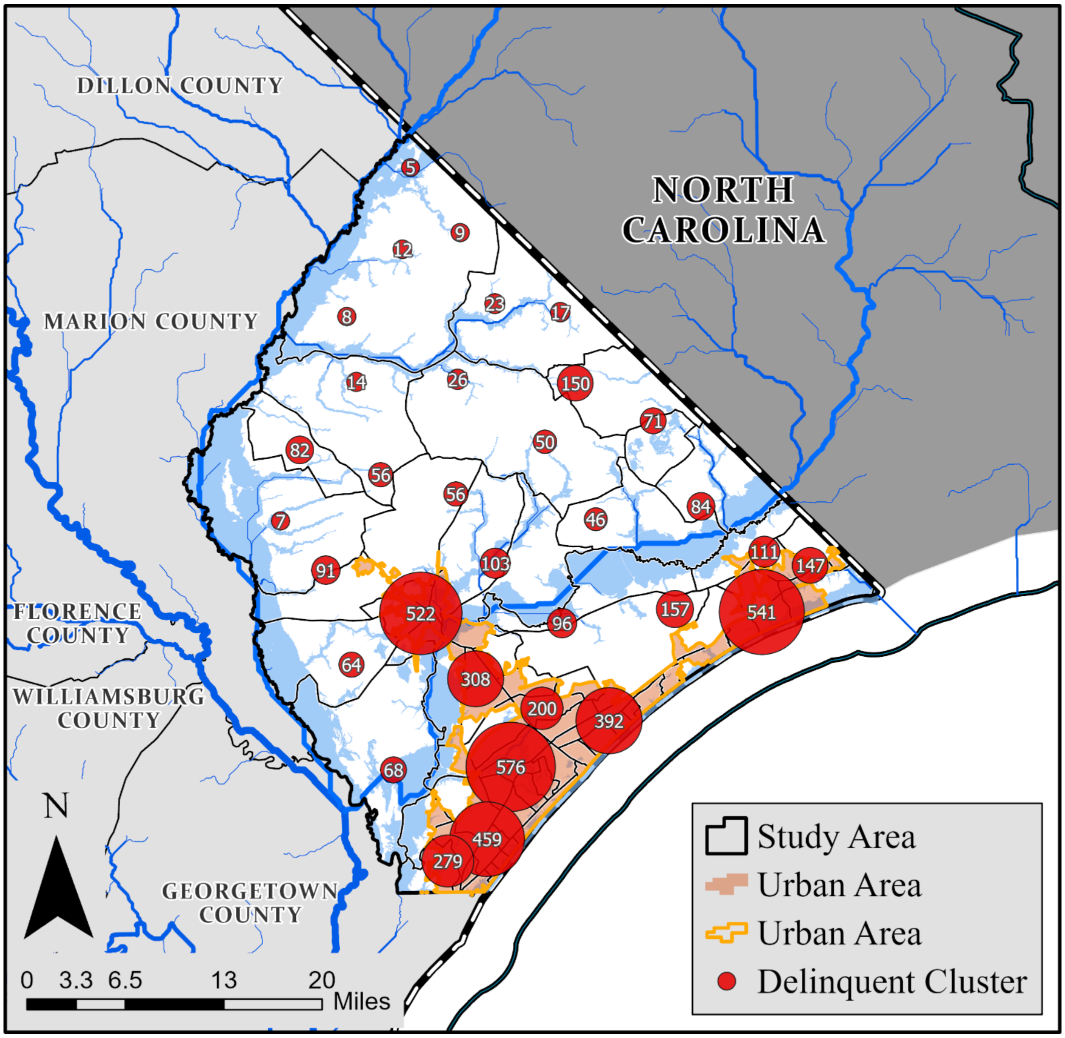

Figure 3.5: Clusters of Properties Delinquent in 2013

point intersected any of those zones it was classified with a 1, otherwise it was classified as 0. Similarly, the points were spatially joined to the 2010 Census Urbanized Area (UA). If the point intersected the UA, it was classified with a 1, and otherwise it was classified with a 0. The last join the dataset underwent was to the 2013 dataset, the start of the record. If the point's Parcel ID was present in the 2013 dataset, it was classified with a 1, and if not was classified with a 0. This allowed for analysis that compared all parcels in the county

during a given year, as well as analysis on the parcels that existed before the flooding disasters took place. The resultant tables for each year were then exported and summarized in Microsoft Excel. In this way, each year has a value for the variables; urban, rural, flood prone, and non-flood prone, as well as the proportion of each subset which are considered delinquent that year.

3.4 Statistical Analysis

Once in Excel, tables summarized the total number of parcels, total delinquent parcels, urban parcels, delinquent urban parcels, rural parcels, delinquent rural parcels, flood prone parcels, delinquent flood prone parcels, non-flood prone parcels, and non-flood prone delinquent parcels for each year. This exercise was completed for all parcels as well as for only those present in 2013. These values were used to calculate the delinquency rate for each subset of parcels. The delinquency rate for any given year represents the delinquent parcels within the subset (e.g. delinquent and urban) divided by the count of the total parcels in the subset (e.g. all urban parcels).

The research questions are concerned with the spatial and temporal nature of delinquency within the county. To explore these concepts at the county-wide scale, three two-proportion Z-Tests were carried out. The first Z-Test explores the hypotheses related to the impact that disaster has on the subsequent years delinquency rate and compares a subset's delinquency rate to the year prior to evaluate whether any significant change happened in that time. The second Z-Test compared whether a subset's delinquency rate was significantly different from the county's total delinquency rate for that year. The third Z-Test was one-tailed and explores the hypotheses related to whether the rural delinquency rate is significantly worse than the urban delinquency rate, as well as whether the flood prone parcel delinquency rate is significantly worse than the non-flood prone delinquency rate.

3.5 Spatial Analysis

To help isolate what areas experienced the most change in delinquency rate at a scale lower than the county level, parcel points along with their classifications were summarized at the Census Tract level using the ESRI's Summarize Within tool. This tool gave every tract an attribute that summed the total number of parcels and the number of delinquent parcels within it. Out of the 72 tracts within Horry County, there were two that had no single-family parcels for 7 years of the record and were removed from subsequent tract-level analysis as they could not inform on how residential delinquency changed over the period of record. The delinquency rates were then calculated for every tract for every year. To measure how a delinquency rate changed within one tract from year to year, additional fields were calculated that measure ($\text{Rate}^{\text{Year 2}}$) – ($\text{Rate}^{\text{Year 1}}$). If a value was positive, it indicates that delinquency rates got higher, and if it was negative, it indicates that delinquency rates improved. The result of this procedure is an attribute for delinquency rate for each year, as well as how the rate changed from the preceding year.

These steps were carried out for only those parcels that existed in 2013 in addition to the full dataset.

The delinquency rate and rate change attributes were subsequently used in ESRI's Cluster and Outlier Analysis (*Cluster and Outlier Analysis (Anselin Local Moran's I) (Spatial Statistics)—ArcGIS Pro, 2022*). The process used Inverse Distance to measure spatial relationships and utilized 499 permutations. The resultant files display tracts that have either relatively high or low values and are surrounded by similarly extreme or significantly different values. This results in 4 map series displaying delinquency rate and delinquency rate change, as well as clusters and outliers for each year's delinquency rate and delinquency rate change.

3.6 Summary

The methods used to investigate this thesis' research questions include both statistical and spatial techniques. The input for these analyses includes annual tax delinquency data at the individual property level within Horry County, which allows for property level classification of urban or rural, as well as by position in the FEMA Special Flood Hazard Area. Statistical analysis compares delinquency rates between these classifications as well as between neighboring years. Spatial analysis is carried out at the Census Tract level, comparing delinquency rates, rate changes, and the spatial autocorrelation of these rates using the Cluster and Outlier Analysis tool.

CHAPTER 4: RESULTS

Section 4.1 is dedicated to the whole-county analysis, including the delinquency rate trends of all parcels, urban parcels, rural parcels, flood prone parcels, and non-flood prone parcels. This analysis is presented in tables which display the counts of properties in each subset, those that are considered delinquent, respective delinquency rates, and lastly the Z-Tests that test the differences between these rates. This paper uses a 95% confidence level within the Z-Tests to evaluate the null hypothesis (the null hypothesis in this case states that the two compared delinquency rates are statistically similar). A P value of a Z-Test with a value under .05 denotes those two delinquency rates are significantly different, rejecting the null.

Section 4.2 of the results is dedicated to the spatial analysis performed at the Census Tract level. This analysis is presented with a map series of each year of the record and is joined with commentary of each year.

4.1 County Wide Analysis

Before analyzing any delinquency, it is interesting to track housing growth in the county with the county’s own GIS data. As seen in Table 4.1, the number of single-family parcels in Horry County increases from 72,121 to 94,517 from 2013 to 2020; giving extra perspective to the housing market in Horry County discussed in Section 3.1. Taken in concert with Figure 3.3, this indicates that home prices steadily increasing

Table 4.1: Horry County Parcel Counts by Classification Subset

All Parcels										
Year	Total Parcels	Total Delinquent	Urban Parcels	Urban Delinquent	Rural Parcels	Rural Delinquent	Floodplain Parcels	Floodplain Delinquent	Non-Floodplain	Non-Floodplain Delinquent
2013	72,121	*4,830*	52,979	*3,128*	19,142	*1,702*	6,071	*380*	66,050	*4,450*
2014	73,646	*6,048*	54,001	*4,005*	19,645	*2,043*	6,105	*455*	67,541	*5,593*
2015	76,600	*5,454*	55,882	*3,681*	20,718	*1,773*	6,238	*424*	70,362	*5,030*
2016	79,171	*5,741*	57,569	*3,888*	21,602	*1,853*	6,331	*461*	72,840	*5,280*
2017	82,508	*4,873*	59,382	*3,161*	23,126	*1,712*	6,457	*404*	76,051	*4,469*
2018	85,537	*4,856*	60,998	*3,151*	24,539	*1,705*	6,568	*393*	78,969	*4,463*
2019	89,387	*4,699*	63,320	*3,008*	26,067	*1,691*	6,713	*378*	82,674	*4,321*
2020	94,517	*4,185*	66,362	*2,666*	28,155	*1,519*	6,891	*344*	87,626	*3,841*
Parcels That Existed In 2013										
Year	Total Parcels	Total Delinquent	Urban Parcels	Urban Delinquent	Rural Parcels	Rural Delinquent	Floodplain Parcels	Floodplain Delinquent	Non-Floodplain	Non-Floodplain Delinquent
2013	72,121	*4,830*	52,979	*3,128*	19,142	*1,702*	6,071	*380*	66,050	*4,450*
2014	70,376	*5,710*	52,098	*3,838*	18,278	*1,872*	5,917	*430*	64,459	*5,280*
2015	71,704	*5,072*	52,823	*3,462*	18,881	*1,610*	6,025	*407*	65,679	*4,665*
2016	71,610	*5,250*	52,804	*3,605*	18,806	*1,645*	6,026	*446*	65,584	*4,804*
2017	71,516	*4,405*	52,769	*2,920*	18,747	*1,485*	6,011	*380*	65,505	*4,025*
2018	71,372	*4,301*	52,692	*2,874*	18,680	*1,427*	5,992	*368*	65,380	*3,933*
2019	71,283	*4,060*	52,650	*2,670*	18,633	*1,390*	5,977	*350*	65,306	*3,710*
2020	71,124	*3,445*	52,572	*2,293*	18,552	*1,152*	5,948	*314*	65,176	*3,131*

and average days on the market decreasing is happening with an increasing supply of single family residential parcels as well.

With that extra context, delinquency patterns can be analyzed more thoroughly. Looking at the whole-county delinquency rates temporally (Table 4.2 Figure 4.1, Figure 4.2), reveals an obvious spike in 2014, followed by a general decline through 2020. As discussed previously, 2014 was a tax reassessment year, the first since the 2009 reassessment that captured home values just a few months after the 2008 financial crisis. This increase in the delinquency rate is seen across 63 of the 70 analyzed tracts when analyzing all existing parcels. The year 2016 is the only other year where there is an increase in the county-wide delinquency rate but unlike the 2014 spike, only 38 of the 70 tracts experienced the increase. This year was notably the first tax year that captures the county after a major flood event in the dataset.

The subsets of urban, rural, and non-flood prone all move in the same patterns with the same approximate magnitude as the overall county throughout the years. Urban parcels are uniformly the lowest delinquency subset, whereas the rural are uniformly the highest. Non-flood prone parcels do not deviate from the whole-county rate. These observations are tested more thoroughly in the Z-Tests in the following sections.

Flood prone is the only subset of parcels where there is an obvious deviation from the other subsets' trajectories. In the years before 2016, this subset was below the whole-county and non-flood prone delinquency rate, but in 2016, those rates intersected. For every subsequent year, the delinquency rate of flood prone parcels was higher than the whole-county rate, as well as the non-flood prone rate.

Table 4.2 Horry County and Subset Delinquency Rates

Delinquency Rate - All Parcels Analysis					
Year	Whole County	Urban	Rural	Floodplain	Non-Floodplain
2013	6.70%	5.90%	8.89%	6.26%	6.74%
2014	8.21%	7.42%	10.40%	7.45%	8.28%
2015	7.12%	6.59%	8.56%	6.80%	7.15%
2016	7.25%	6.75%	8.58%	7.28%	7.25%
2017	5.91%	5.32%	7.40%	6.26%	5.88%
2018	5.68%	5.17%	6.95%	5.98%	5.65%
2019	5.26%	4.75%	6.49%	5.63%	5.23%
2020	4.43%	4.02%	5.40%	4.99%	4.38%
Delinquency Rate - 2013 Parcels Analysis					
Year	Whole County	Urban	Rural	Floodplain	Non-Floodplain
2013	6.70%	5.90%	8.89%	6.26%	6.74%
2014	8.11%	7.37%	10.24%	7.27%	8.19%
2015	7.07%	6.55%	8.53%	6.76%	7.10%
2016	7.33%	6.83%	8.75%	7.40%	7.32%
2017	6.16%	5.53%	7.92%	6.32%	6.14%
2018	6.03%	5.45%	7.64%	6.14%	6.02%
2019	5.70%	5.07%	7.46%	5.86%	5.68%
2020	4.84%	4.36%	6.21%	5.28%	4.80%

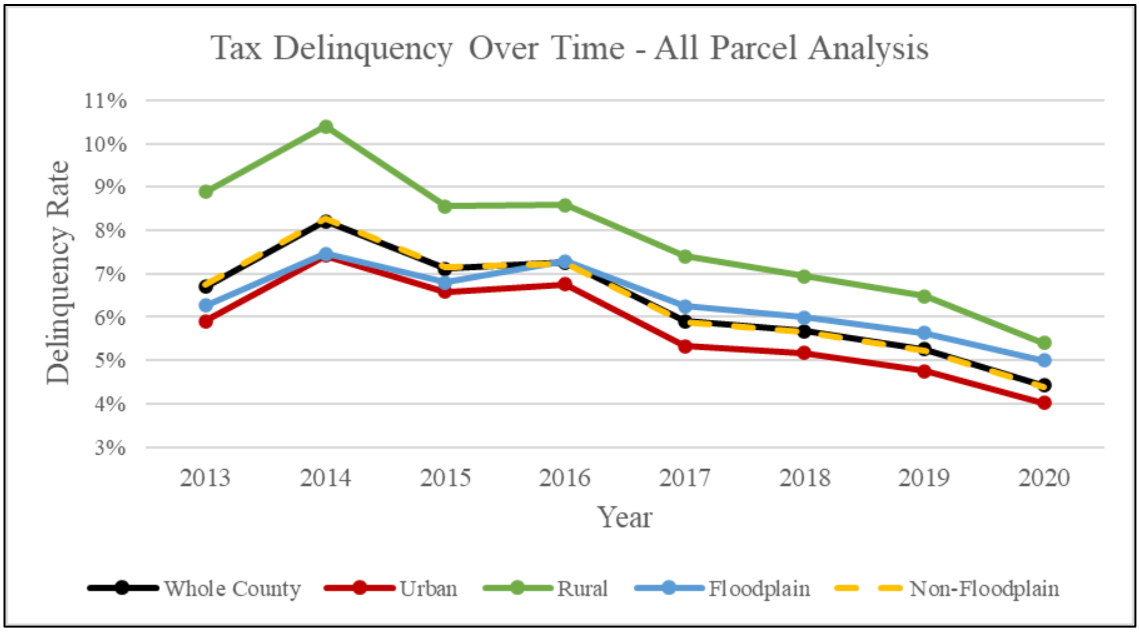

Figure 4.1: County and Subset Delinquency Trajectories of All Parcels

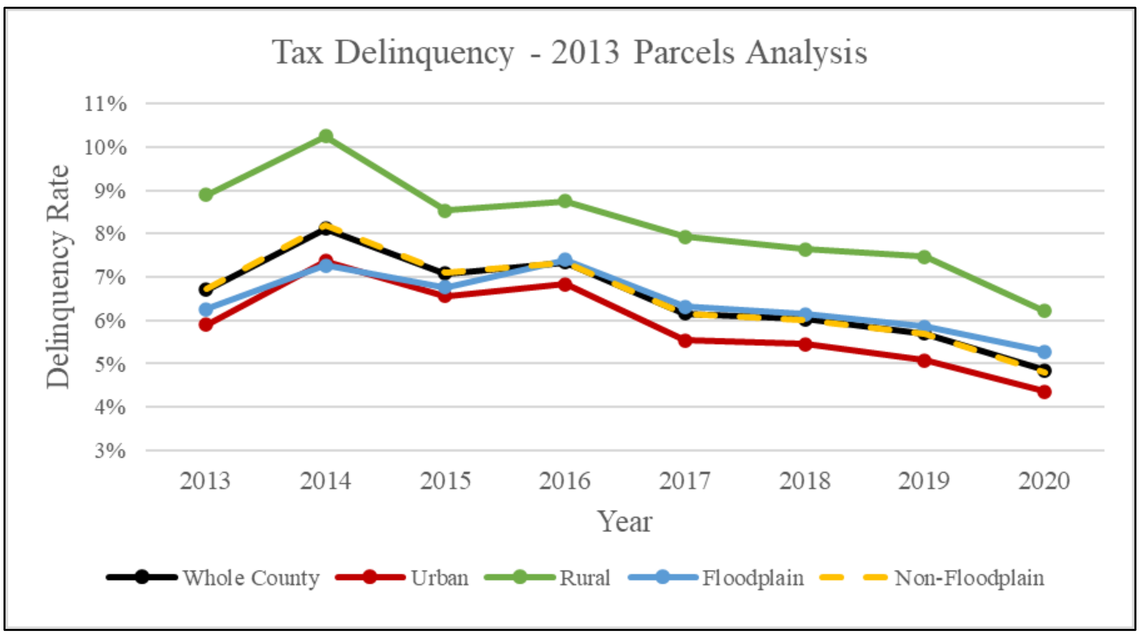

Figure 4.2: County and Subset Delinquency Trajectories of Parcels Existing in 2013

To further isolate how the floods of 2015 seem to have impacted the trajectory of some parcels, Figure 4.3 displays the difference in average delinquency rates for all tracts that experienced a 2016 increase in delinquency, as well as tracts that saw a 2016 decrease or no change in the delinquency rate. Those tracts that experienced the increase in 2016 had a lower average delinquency rate prior to 2016 compared to those tracts that witnessed the 2016 decrease, which contrasts the notion that areas with more delinquency are more prone to future increased levels of delinquency. In 2017, the averages become more similar for the remainder of the record. When only analyzing those parcels that existed in 2013, the tracts with the 2016 increase also show separation in 2018, with a lower delinquency rate. The following sections explore Z-Tests that analyze these observed trends year to year, as well as comparing different subsets of parcels in the county to analyze broadly what contributes to these changes on an annual basis.

4.1.1 Z-Test: Yearly Change

Two-tailed Z-Tests were used for the whole county as well as each subset (urban, rural, flood prone, non-flood prone) to compare one year to the year immediately preceding it. The resultant Z-Test P values are displayed in Table 4.3. For each subset as well as the overall county, 2016 was the only year that was uniformly not considered significantly different from the year preceding it. The flood prone parcels show no significant change for the years of 2015, 2016, 2018, 2019, and 2020. This is the only subset that shows this strong pattern, although the urban subset and not-flood prone subsets showed no significant change during 2018. These trends largely remain true when only analyzing parcels that existed in 2013 with the exception of 2018, which becomes more like 2016 and shows no significant changes in any of the subsets.

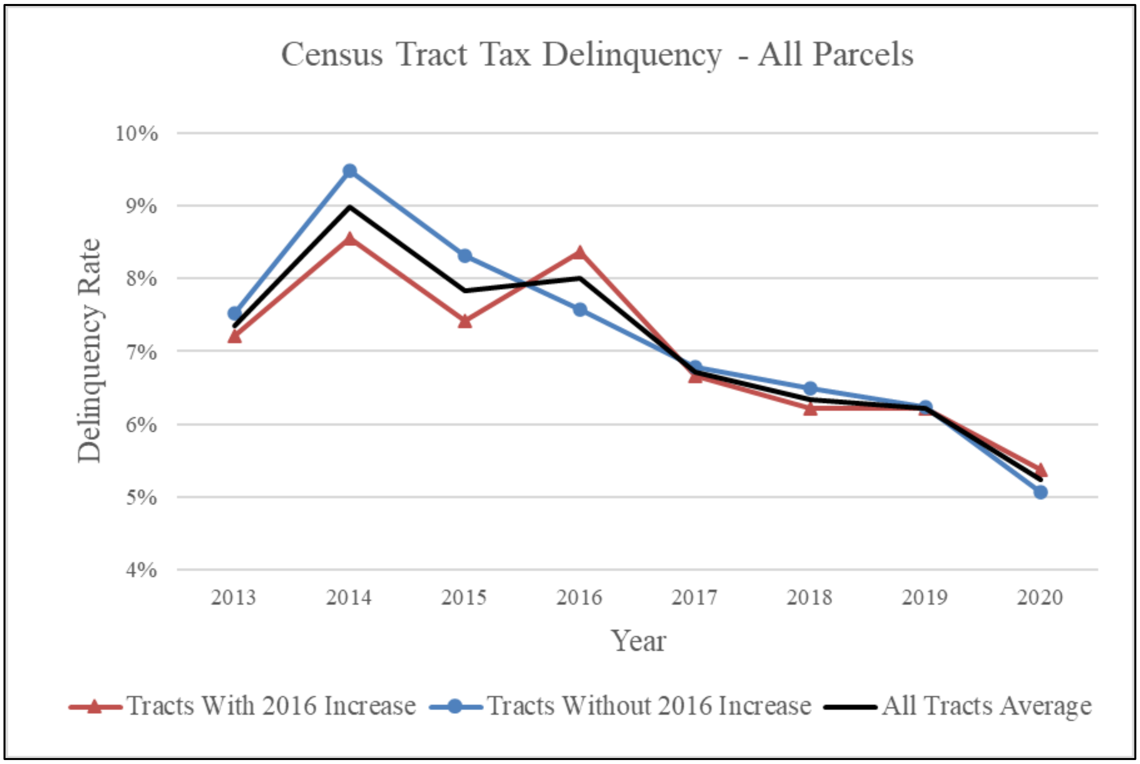

Figure 4.3: Average Delinquency of Tracts Classified by 2016 Change

Table 4.3: Two-Tailed Z-Test P Values – Year to Year Change

Two-Tailed Z-Test - Year to Year Change

The tables below compare the rate of delinquency of a subset to the same subset the prior year.
(Is 2014's urban delinquency rate significantly different from 2013's)
A P-Value less than .05 signifies the years are significantly different (Shaded cells).

	All Parcel Analysis					**2013 Parcel Analysis**				
Year2 - Year1	*Whole County*	*Urban*	*Rural*	*Flood Prone*	*Non-Flood Prone*	*Whole County*	*Urban*	*Rural*	*Flood Prone*	*Non-Flood Prone*
2014 - 2013	***0.000***	***0.000***	***0.000***	***0.006***	***0.000***	***0.000***	***0.000***	***0.000***	***0.018***	***0.000***
2015 - 2014	***0.000***	***0.000***	***0.000***	0.085	***0.000***	***0.000***	***0.000***	***0.000***	0.145	***0.000***
2016 - 2015	0.158	0.139	0.468	0.146	0.232	***0.030***	***0.043***	0.204	0.085	0.060
2017 - 2016	***0.000***	***0.000***	***0.000***	***0.010***	***0.000***	***0.000***	***0.000***	***0.001***	***0.009***	***0.000***
2018 - 2017	***0.022***	0.121	***0.017***	0.252	***0.029***	0.146	0.295	0.127	0.340	0.165
2019 - 2018	***0.000***	***0.001***	***0.011***	0.186	***0.000***	***0.004***	***0.004***	0.230	0.253	***0.005***
2020 - 2019	***0.000***	***0.000***	***0.000***	***0.041***	***0.000***	***0.000***	***0.000***	***0.000***	0.079	***0.000***

4.1.2 Z-Test: Whole County Compared to Subsets

There are obvious trends for the Z-Tests comparing a given subset's delinquency rate to that of the whole county (Table 4.4). Both the delinquency rate of the urban and rural subsets is significantly different from the county's rate for all years on the record, although in different directions. The delinquency rate of urban parcels is uniformly lower than the county rate, whereas the rural parcels' rate is uniformly higher. There is no tidy significant distinction for the subsets of flood prone and non-flood prone parcels. Out of the two subsets, only two years of the flood prone subset (2014 and 2020) are significantly different at the 95% confidence interval, reaffirming the observations of a pattern reversal from Figures 4.1 and 4.2. Although the P values for flood prone and non-flood prone largely remain below that 95% confidence threshold there is a reversal that occurs in 2016. Flood prone properties have a lower delinquency rate than the whole county for all years preceding 2016, but the opposite is true for all subsequent years. The inverse is seen for the non-flood prone subset. Once again, these trends are not statistically significant.

When examining just those parcels that existed in 2013, these trends are identical with the exception of the 2020 flood prone value falling below the 95% confidence threshold. This analysis points towards conclusion that there are general locational attributes that can contribute to delinquency, namely along the urban-rural classification.

4.1.3 Z-Test: Opposing Subsets Compared

One-tailed Z-Tests exploring the hypotheses related to the relative delinquency rates between opposing subsets expected that rural parcels would have a higher relative delinquency rate compared to urban parcels, and that the same would be true between

Table 4.4: Two-Tailed Z-Test P Values – Subsets Compared to Whole County

Two-Tailed Z-Test - Subsets Compared to Whole County

The tables below compare the rate of delinquency of a subset to the county total within the same year
(is 2013's urban delinquency rate significantly different the entire county's rate)
A P-Value of less than .05 signifies that the subset is significantly different from the county's rate (Shaded cells).

	All Parcel Analysis				**2013 Parcel Analysis**			
Year	*Urban*	*Rural*	*Flood Prone*	*Non-Flood Prone*	*Urban*	*Rural*	*Flood Prone*	*Non-Flood Prone*
2013	***0.000***	***0.000***	0.094	0.383	***0.000***	***0.000***	0.094	0.383
2014	***0.000***	***0.000***	***0.019***	0.320	***0.000***	***0.000***	***0.011***	0.301
2015	***0.000***	***0.000***	0.170	0.416	***0.000***	***0.000***	0.177	0.417
2016	***0.000***	***0.000***	0.464	0.492	***0.000***	***0.000***	0.421	0.482
2017	***0.000***	***0.000***	0.125	0.401	***0.000***	***0.000***	0.308	0.454
2018	***0.000***	***0.000***	0.151	0.412	***0.000***	***0.000***	0.359	0.467
2019	***0.000***	***0.000***	0.093	0.389	***0.000***	***0.000***	0.304	0.453
2020	***0.000***	***0.000***	***0.014***	0.322	***0.000***	***0.000***	0.067	0.366

flood prone parcels and non-flood prone parcels. A P-value less than .05 indicates with 95% confidence that the hypothesized relationship (HA) exists; HA alleges that rural parcels carry a higher delinquency rate than urban and that flood prone parcels carry a higher delinquency rate than non-flood flood prone parcels. When comparing the urban and rural subsets in Table 4.5, all years exhibit the hypothesized relationship with over 95% confidence. This remains true when only considering parcels that existed in 2013. When comparing flood prone and non-flood prone subsets, only 2020 exhibits the hypothesized relationship. When analysis is limited to 2013 parcels, this significance disappears. In 2014, the delinquency rate of non-flood prone parcels is significantly higher than delinquency rate of flood prone parcels. This is in direct contrast to the hypothesized relationship but notably takes places before any of the major flooding events.

4.1.4 Summary: Whole County Analysis

The analysis to this point has only looked at parcels aggregated to the county level. At this macro-scale, longitudinal analysis has revealed the overarching trends of tax delinquency in the county. Even in those years preceding the disaster events, this is not a constant phenomenon year to year. Along with this observation, there are also classification-based disparities between the urban and rural parcel subsets, whereby the rural Parcels are uniformly more likely to be considered tax delinquent. Interestingly, no such clear trend exists when comparing flood prone properties to non-flood prone properties. This could be because those areas are considered more desirable to live in, therefore it is worth it to continue investing in the property, or it could indicate that the FEMA Special Flood Hazard Area is not representative of the impacted areas associated

Table 4.5: One-Tailed Z-Test P Values – Subsets Compared

One-Tailed Z-Test - Opposing Subsets Compared				
The table below compares the rate of delinquency of a subset to an opposed dataset (HA: Urban < Rural) (HA: Non-Flood Prone(Non-FP) < Flood Prone) A P-Value less than .05 signifies that the hypothesized relationship (HA) exists (Shaded cells)				
	All Parcel Analysis		**2013 Parcel Analysis**	
Year	*HA: Urban < Rural*	*HA: Non-FP < Flood Prone*	*HA: Urban < Rural*	*HA: Non-FP < Flood Prone*
2013	***0.000***	0.077	***0.000***	0.077
2014	***0.000***	0.012	***0.000***	0.006
2015	***0.000***	0.150	***0.000***	0.157
2016	***0.000***	0.461	***0.000***	0.414
2017	***0.000***	0.107	***0.000***	0.292
2018	***0.000***	0.132	***0.000***	0.348
2019	***0.000***	0.077	***0.000***	0.288
2020	***0.000***	***0.009***	***0.000***	0.051

with the floods. This may be because the floods exceeded the 100-Year threshold, or it may be that the models don't adequately capture flood risk.

4.2 Census Tract Analysis

A look at the trajectory for all tracts in in the county in Figure 4.4 reveals the variability that tax delinquency has across the county. While most tracts loosely follow the trajectory of the county at large, there are tracts who have years of exaggerated or inversed change. To determine specifically where these patterns occur, each year's delinquency rate and rate change were mapped, as well as analyzed for clusters and outliers. These results are covered in Section 4.2.1, followed by Section 4.2.2 which provides some more context around the Socastee and Bucksport Communities.

4.2.1 Cluster Analysis of the County

Delinquency Rate Change maps were symbolized with classified values, whereby a value under 2.5% change was classified as an increase or decrease depending on the sign of the value. Values over 2.5% were considered a large change in the appropriate direction. This constant scale allows for a comparison year to year on change across the county. The results of Census Tract level analysis are located in Figures 4.5 – 4.8, which presents map series by year. Figures 4.5 and 4.6 display the maps where all existing parcels were included in analysis, and Figures 4.7 and 4.8 show the results of analysis performed on those parcels that existed in 2013.

For 2013, the start of the record, the lowest delinquency is seen along the coast. Tracts further inland, especially along the North Carolina border had exceptionally high delinquency. Cluster and outlier analysis mirror this understanding but do pick out a few

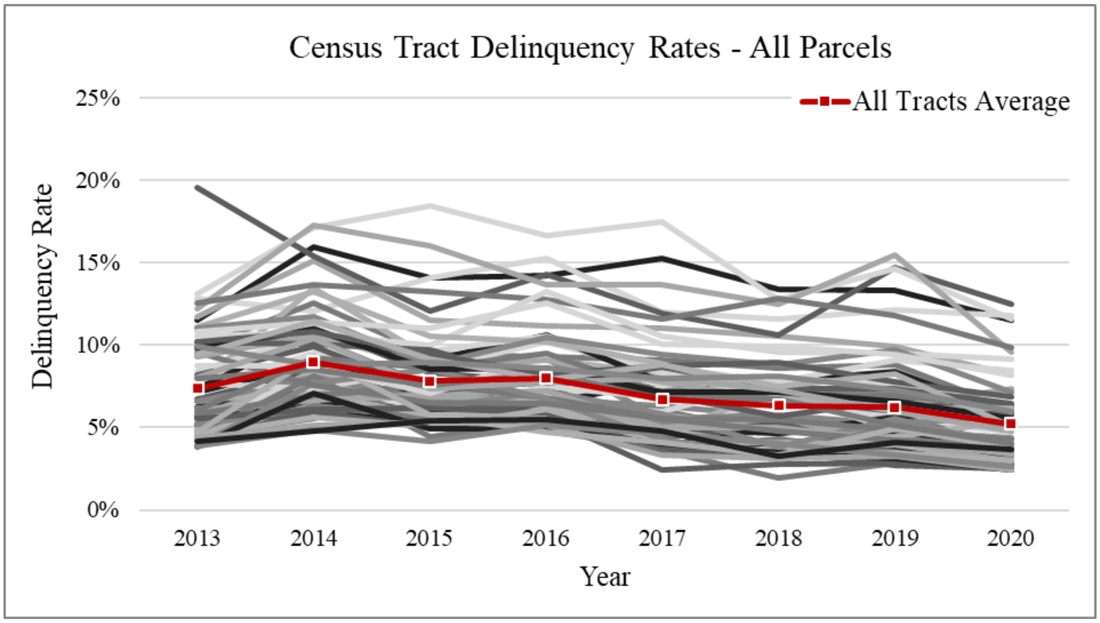

Figure 4.4: Delinquency Rates of All Parcels in All Census Tracts

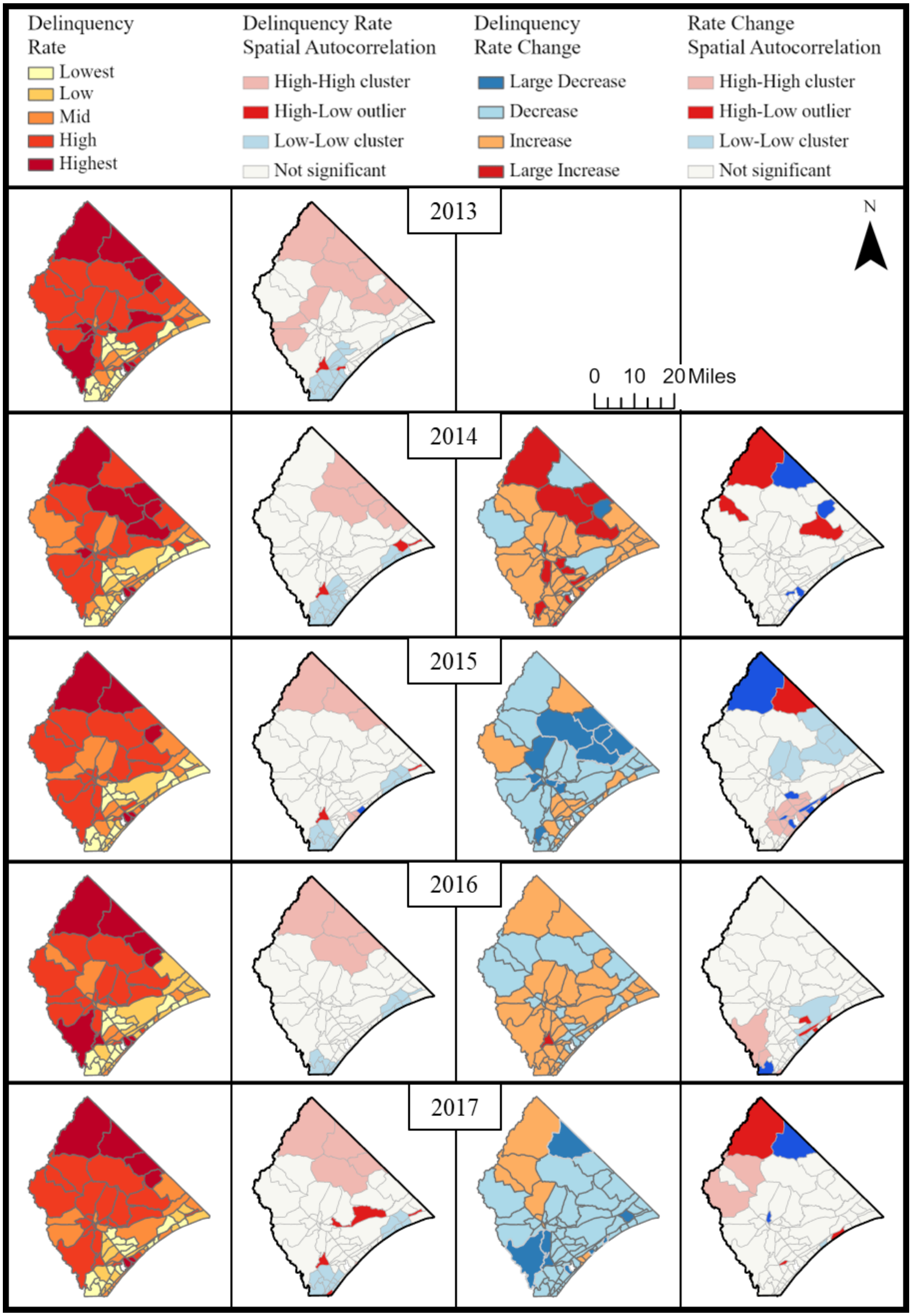

Figure 4.5: Tract Tax Delinquency Analysis Map Series of All Parcels, 2013-2017

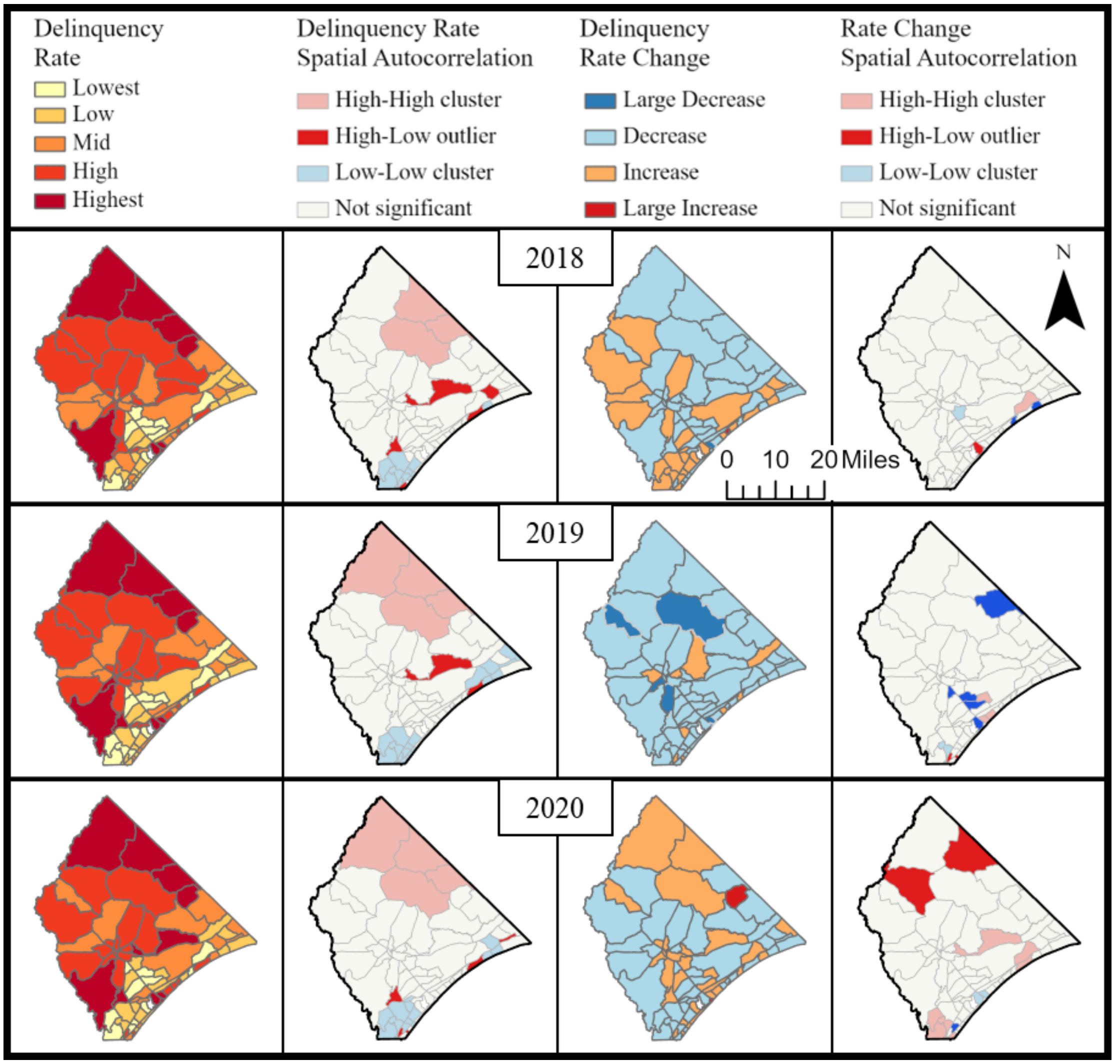

Figure 4.6: Tract Tax Delinquency Analysis Map Series of All Parcels, 2018-2020

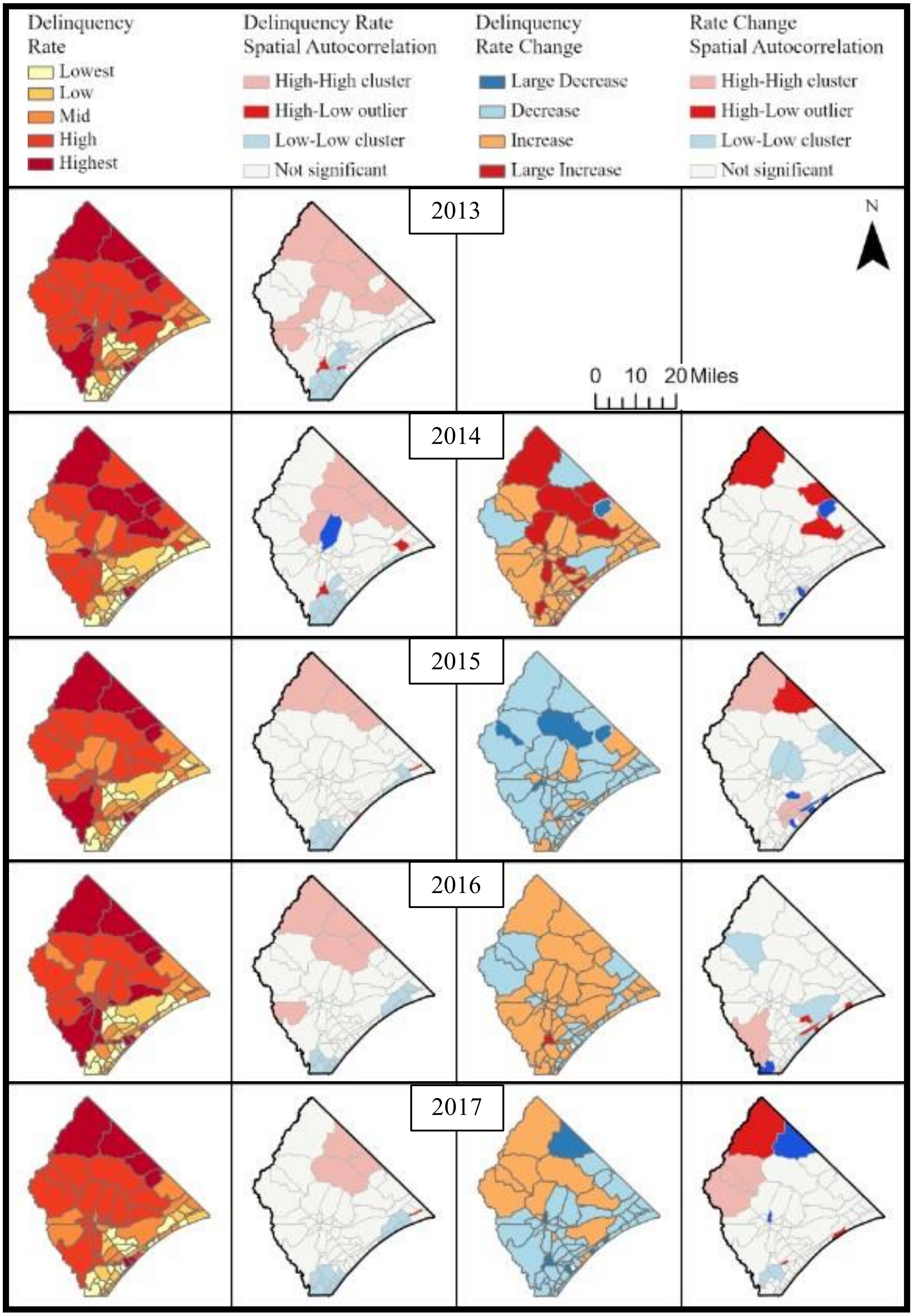

Figure 4.7: Tract Tax Delinquency Analysis Map Series of 2013 Parcels, 2013-2017

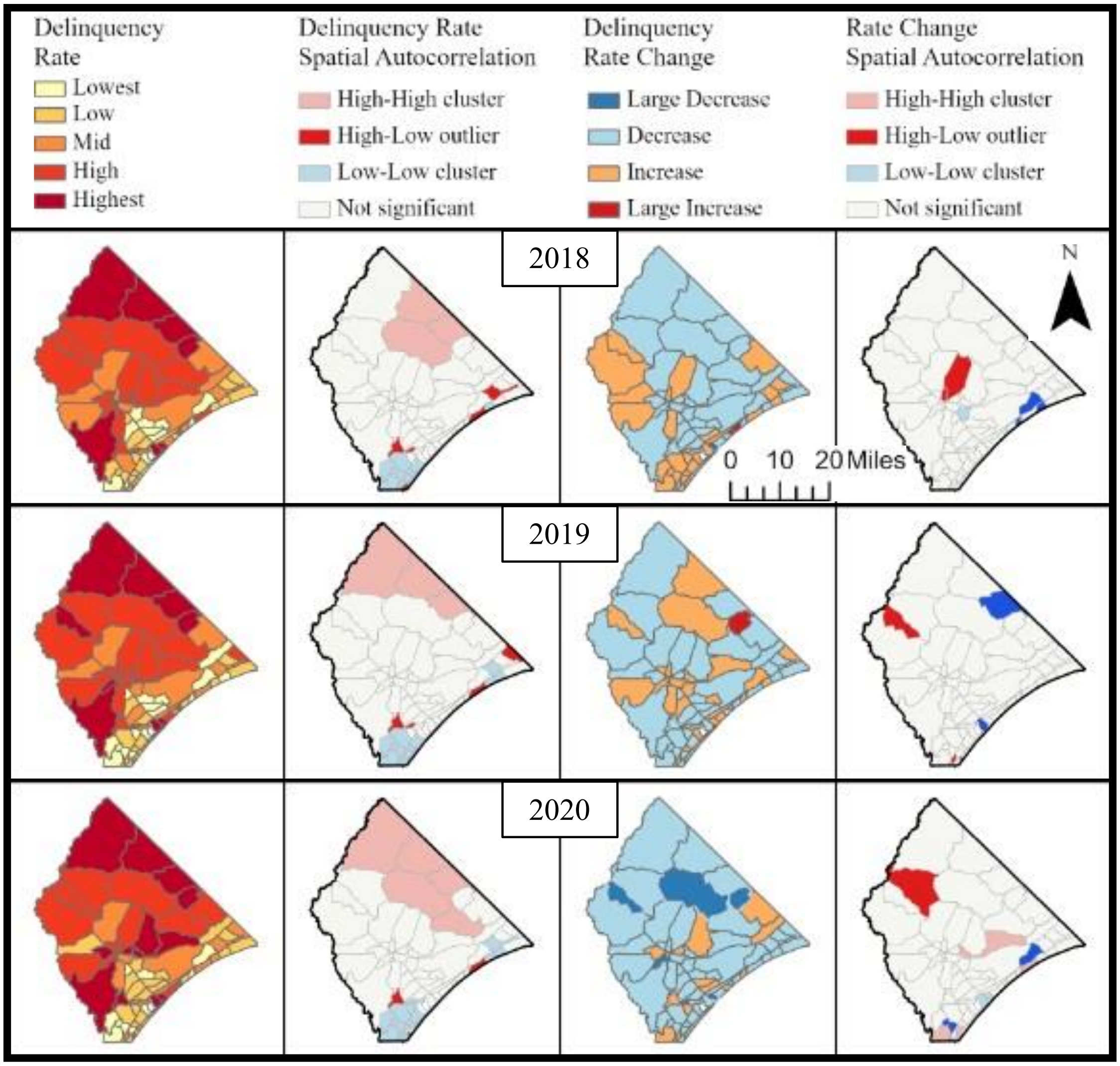

Figure 4.8: Tract Tax Delinquency Analysis Map Series of 2013 Parcels, 2018-2020

tracts in an area referred to as Socastee as being statistical outliers with high delinquency rates compared to those tracts surrounding them.

The year 2014, the year of the tax reassessment, shows the distribution of delinquency rates remain similar to 2013, although the rate change maps show that almost the entire county experienced an increase in delinquency. There are no clusters of relatively high or low changes in the county, although there are some statistical outliers mostly in the rural areas in the North of the county.

The year 2015 brings some relief as most tracts show a delinquency rate decrease. The distribution across the county remains similar to prior years, where inland-rural areas see higher rates of delinquency compared to the coast. Areas connecting Conway to the coast are considered a high-increase cluster, although there are outliers within the area. Areas north of Conway, along the Waccamaw River constitute a high-decrease cluster. When only considering properties that existed in 2013, the northern corner of the county sees a relatively high increase in delinquency. When considering all properties, this area sees a high decrease in delinquency.

In 2016, the first year after the floods of 2015, brings an interesting set of results. The north of the county becomes unified as a high delinquency cluster, while perennial outliers near Socastee fall out of significant difference compared to their neighbors. For the first time in the dataset, areas along the southern end of the Little Pee Dee River near the south of the county become a high increase cluster.

The year 2017 is similar to 2016 in that it is the first year after a major flooding event. Dissimilar though, is the fact that it comes on the heels of another flood, and therefore some of some of the areas impacted severely in 2016 are not experiencing a completely novel shock. In this event, areas farther upstream on the Pee Dee now constitute a high increase cluster. When analyzing all existing parcels, some areas along the Waccamaw and a tract near Socastee emerge as high delinquency outliers for delinquency, but this significance drops when only looking at parcels that existed in 2013.

In 2018 there are slight changes in the high delinquency clusters near the north of the county, but high delinquency outliers along the Waccamaw persist. Although 2018 is relatively static year, without many tracts being considered significant clusters or outliers of the delinquency rate change. One tract near Socastee is picked out as a significantly high delinquency outlier for the first time since 2014 and continues this distinction throughout 2020.

The year 2019 is a unique year in the dataset, as it is both another tax reassessment year and it comes after the floods of 2018. The county is also still recovering in some capacity from the floods of 2015 and 2016, therefore the changes in tax delinquency that were spurred by those events should not be expected to repeat in 2019, although they may be exacerbated. Unlike 2014's tax reassessment, 2019 did not seem to interrupt the housing market in Horry County, and the county sees a continued general decline in delinquency. There are very few significant tracts picked up in the cluster and outlier analysis of delinquency rate change, although the north of the county remains a high delinquency rate cluster, and the southern corner remains a low delinquency cluster.

The last year in the dataset, 2020, continues a decrease in delinquency for large parts of the county. The distribution of delinquency doesn't see a marked change, although some areas along the Waccamaw that were perennial high delinquency outliers were identified as being high increase clusters.

4.2.2 A Focus on Socastee and Bucksport

It is easy to look at a map series such as Figure 4.5 and forget to consider what these communities look like in real life. To ground truth these maps, Figure 4.9 shows a larger scale view of the Socastee and Bucksport areas with a heavily clustered depiction of 2016 delinquent properties. This clustering is used to protect the identity of those property owners who were considered delinquent but helps display where delinquency occurred in both a suburban and rural area. This area, specifically the area west of the river, is identified in Figure 4.5 as being a cluster where high delinquency rate change was surrounded by similarly high values. These two neighboring areas are close together on a map but could not be further apart from each other in terms of human landscapes. Hence, they offer insight into what impact flooding has on different community archetypes. Both Socastee and Bucksport are different in 2022 because of the floods of 2015, 2016, and 2018, but those changes have likely manifested in different ways

Socastee is not included in that high increase cluster, but the area did have a large increase in delinquency in 2016 and is currently enrolled in the buyout program facilitated by the South Carolina Office of Resilience. Structures are similar to what you'd expect in a highly suburban area outside of a burgeoning population center. Even with the resources that typically accompany that type of community, the county is pursuing an arduous home buyout program in 2022 because of the lingering flood

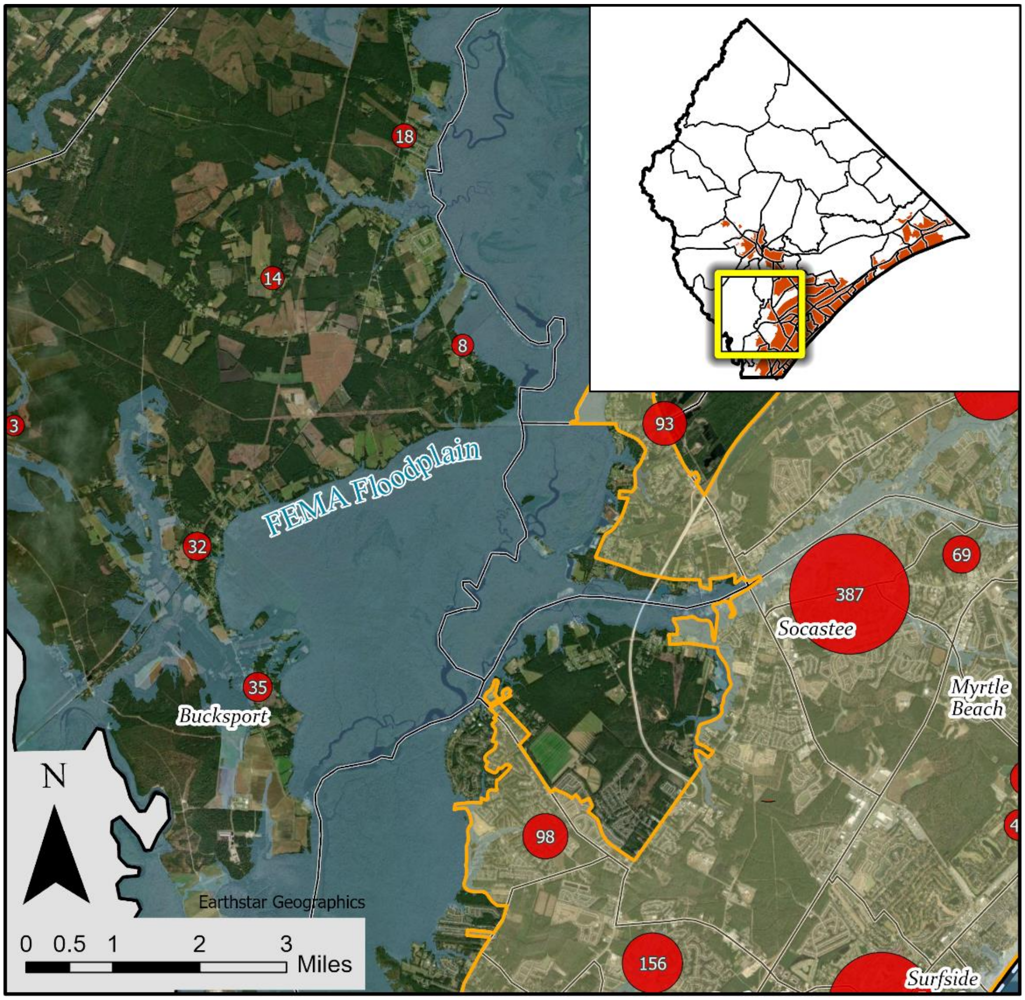

Figure 4.9: Bucksport and Socastee Delinquency Clusters in 2016

impacts and fatigue from the past decade. Even as certain homeowners undergo that process, some homeowners enrolled in the program choose to sell the property to the market instead of using the government's buy out because they can get a higher price in a shorter time.

Socastee is fortunate to have the population, profile, and resources to encourage the county to pursue federal and state recovery programs, but even with these programs flooding has spurred homeowners' decisions to sell their property and move. This signals a changing face of the community, which begs the question of where this population is moving and who is taking their place.

Unlike Socastee, areas near Bucksport are intensely rural, and 35 homes being delinquent equate to a huge proportion of the area's housing stock. When this area was discussed with the Horry County Tax Assessor, he commented that this area is home to a large portion of the county's minority population (L. Roscoe, personal communication, April 13th). As discussed in the literature review, race is a factor that frequently helps to make disaster impact and recovery more severe. How these factors of being a racial minority and in a rural setting interplay can be extrapolated from other studies, but stories of how individual and group agency of community members remains invisible without designated study efforts.

Bucksport does not share the visibility or status of Socastee, and thus has not garnered as much attention as its neighbor across the river in the eyes of larger institutional recovery efforts. Further, low housing stock makes relocating in the community seem challenging, and the ability to sell a property for an adequate price unlikely which begs the question of if, where, and why people have either relocated or recovered in place. Tax delinquency data has identified it as an area that could use additional research especially with attention given to race and rural challenges.

4.3 Summary

Just as the whole-county analysis revealed the overarching trends of delinquency in the county year-to-year, the Census Tract analysis reveals the spatial patterns of delinquency within Horry. Perennially, the northern portion of the county are the some of the highest delinquency areas, whereas the southern corner and areas nearest the coast are the lowest. The year 2014 sees a widespread increase in delinquency for virtually the entire county that is most likely tied to the property value reassessment. 54% of tracts experience an increase in 2016, and areas along the lower Little Pee Dee comprise a high increase cluster in the wake of the 2015 floods. In 2017 there is some rebound in these areas, although a few tracts along the Waccamaw River become high delinquency outliers when evaluating all parcels. It appears the rural and northern parts of the county are habitually high delinquency, but areas along the Pee Dee and Waccamaw see some more variability in both delinquency rate and rate change. Tracts near the south of the county that become repeated high delinquency outliers point to those areas that were most impacted by the natural hazards. By understanding where these changes in delinquency occurred, areas like Socastee and Bucksport can be studied more rigorously to uncover the nuance of housing recovery in Coastal South Carolina.

CHAPTER 5: CONCLUSION

This thesis has been founded on decades of research on community trajectory and disaster recovery. That base of knowledge was joined with a unique and understudied area of South Carolina that was recently subject to three major flooding events in order to localize these understandings to a novel place. The combination inspired research questions that employ GIS methods to establish a starting baseline of tax delinquency in the study area, and the need to track the nature and distribution of property tax delinquency using statistical and spatial analysis. The variable of tax delinquency is used to signal a lack of continued upkeep to a property, and therefore a type of community decline. Residential tax delinquency is a process that can impact a community in the long term as neighboring property values suffer. However, in the short-term tax delinquency spurs a property owner's two-year process that can ultimately result in the tax sale of the property. The results of analysis point to temporal inflection points for the county in terms of tax delinquency, locational attributes that carry differing risks of tax delinquency, and to geographic hotspots around the county that reacted unusually compared to neighboring areas after major flooding events.

5.1 Research Questions Revisited

To understand how the county's tax delinquency changed in the years after major flooding, two research questions focused the creation of methods to form a pre-flooding baseline as well as track how the distribution and nature of delinquency changed through the end of the data record (2020).

1. What was the spatial variation in housing vacancy prior to the 2015 floods?
2. How did the spatial pattern change during the period of record (2013-2020)?

Research question one used the years of 2013, 2014, and 2015 as a baseline, as 2016 was the first tax year after a major flooding event. This uncovered an unexpected and widespread increase in delinquency in 2014, which helped to accentuate that communities are always changing, with or without disaster events. This baseline also helped show that the northern rural portions of the county were habitually the most delinquent, whereas the coastal urban areas had the lowest delinquency rates.

Statistical analysis confirms that during this baseline, rural parcels are significantly higher delinquency than their urban counterparts, which was expected given population pressure in urban areas. Unexpectedly however, flood prone parcels were lower delinquency than those outside of this high-risk area before any flooding events. It was hypothesized in Section 1.2 that the environmental risks of being in a floodplain would drive delinquency rates higher, but this miscalculation helps prove that baseline place-based context assists analysis when evaluating a study area.

Research question two continues analysis through the year 2020 and does pick up on some interesting patterns. It was hypothesized that there would be increases in delinquency following the three flooding events, but it seems the only year where there was widespread delinquency after the baseline period followed the first flooding event. It was also hypothesized that areas with more preexisting delinquency would have increased rate changes relative to other tracts following these events, but analysis done on the 54% of tracts that experienced an increase after 2015 showed that there was a lower average preexisting delinquency than the tracts that saw a decrease in the same year (Figure 4.3). After this shock, these tracts' average did decline for the remainder of the study period and dropped below the rates of the baseline period by the year 2017.

Parcels in the rural subset remained consistently above the urban subset for the entire period just as it did during the baseline. Contrary to the baseline, the flood prone subset's delinquency rate overtakes the non-flood prone subset in 2016, a pattern that strengthens over the rest of the period. This realigns the subset with the hypothesized results that were incorrect for the baseline period.

5.2 Discussion

Upon the completion of analysis, the results were shared with the Horry County Tax Assessor (L. Roscoe, personal communication, April 13th). His discussion and feedback help to inform and ground truth the following discussion.

Shocks such as flooding have been shown to alter a community's trajectory, although traditionally literature has explored these shocks on population centers, such as New Orleans or Miami-Dade (Lee, 2017). Utilizing Horry County has provided a unique look at how local housing is impacted within a coastal South Carolina context, and Horry County specifically is a unique study area given its burgeoning population, intense development, and large rural area. To explore this phenomenon, the research questions probe into the landscape of community trajectory with tax delinquency of single-family homes in Horry County amidst three Major Disaster Declarations. Analysis was performed on individual parcel's tax delinquency for the years of 2013 through 2020. Each parcel was appropriately classified based on its position related to the FEMA Special Flood Hazard Area (SFHA) and position related to the Myrtle Beach—Socastee Urbanized Area. These classifications were targeted to specifically explore hypotheses that rural parcels are more likely to be delinquent than urban, as well as whether parcels in the SFHA were more likely to be delinquent than those not in that administrative zone.

The results of Z-Test analysis indicate that rural parcels are uniformly worse off than urban, but there was no consistent distinction for flood prone and non-flood prone parcels. When considering all parcels in existence, flood prone parcels had a significantly lower delinquency rate than the whole county in 2014, a year where the majority of the county saw a marked increase in delinquency. This trend then saw a reversal starting in 2016 and strengthened until when in 2020 the flood prone parcels carried a significantly higher delinquency rate. This seems to signal a longer-term shift in property valuation and investment in the county. In 2014, flood prone parcels were less likely to be delinquent than almost any other subset (only excluding urban parcels). Therefore, these parcels were among the most likely to have owners investing in maintaining the residential property. That pattern reversal starting after the floods of 2015 indicates an increased potential for owners in the floodplain to stop investing in their properties, a trend that occurs in no other subset. Further, when analyzing only parcels that existed in 2013, that trend remains, but to a lesser magnitude.

This hints to a potential for newer properties in the floodplain to carry extra potential for tax delinquency, which beckons to ask how responsible it is to continue living in high-risk areas, as well as to permit developers to continue to build new homes in the SFHA. In the 8 years of the study period, an additional 820 homes were in constructed in the SFHA, a nearly 14% increase. When asked for his opinions on this statistic, the Tax Assessor did mention that there are recent developments to the building codes which have increased freeboard requirements to 3 feet above the flood levels experienced in 2018. While free board requirements are indeed a step in the right direction, it is worth noting these properties will still face issues of access during times of flood, as well potentially increase downstream effects related to land use change. Regardless of the institutional guiderails that indicate risk, perceptions of certain flood prone areas have irreparably changed within the county, with residents occasionally taking risk communication into their own hands such as the Socastee resident in Figure 5.1.

Horry County's population growth estimates and the finding that structures in the SFHA were significantly less likely to be delinquent than the rest of the county in the year 2014, lends credibility to idea that home buyers may see more value in properties within Horry County when they are near the water, especially when the dread of flooding is foreign. If this is the reality, then it raises questions of where the displaced inhabitants found themselves after becoming delinquent or being forced to sell their property to those with more resources, and how the heart of the afflicted communities may change as original owners are replaced with unknown neighbors who do not carry the same risk perceptions.

This thesis explores concepts of how locational characteristics such as a parcels position in an urban setting or in a floodplain impacts the delinquency rate, but there is valuable information hiding in the intersection of high-risk categories. Although valuable

Figure 5.1: Socastee Resident's Posted Warning (P. Kendrick, personal communication, June 20, 2022)

insight has come from the analysis completed within the scope of this paper's research, such as uncover trends that flood prone properties have undergone since 2016, that trend may be even stronger in rural-flood prone parcels or urban-flood prone areas. Exploring the interplay of these categories can help further isolate challenges that the county is facing, which can help recovery efforts target the homeowners that they most critically need to. Further, socioeconomic data can help target the parts of the population that are disproportionately afflicted with tax delinquency during years where there are shocks related to natural hazards.

Subsequent to the whole county analysis, Census Tract analysis then explored local changes in tax delinquency rates to see where in the county changes were happening and when, revealing hotspots and outliers of high and low delinquency frequently outside of the urban area.

This further highlights the use in evaluating an entire county, including its rural contingent. When evaluating the delinquency for both the overall county and individual tracts, there was the widespread spike in 2014, possibly coinciding with the property value reassessment and a change in local administration in the Tax Assessment Office. This constitutes the first real "shock" to Horry County housing delinquency during the study period. The reassessment in 2014 was the first reassessment since 2009 where property values may have dropped in the beginning waves of the 2008 financial crisis. According to the communication with the Tax Assessor, assessed values in 2009 were increased relative to 2004 values, so increased property values were not new in the community. That said, increased property values logically correlate to higher taxes, a prospect that could have led to the sharp increase in delinquency for 2014. The Tax

Assessor also expressed that there may have been a backlog of delinquency from the previous year, inflating 2014's high values. This gives weight to the notion that communities are constantly in flux, and that community change can be driven by factors other than flood damage. Regardless of the exact reason, 2014 saw a marked increase in delinquency across the county, indicating a level of increased stress in communities and an increase in property disinvestment. The floods of 2015 then appear to be a true secondary shock to the housing landscape within Horry County, pushing previously low-delinquency areas above those tracts who were most impacted in 2014.

To highlight the use of spatial analysis and data visualization, the first tax year after the floods of 2015 draws attention to a high delinquency rate change cluster along the southern corner of the county along the Little Pee Dee River. If the change in the area is truly tied to the floods, then it immediately signals areas where floods are going to have years of lasting impacts on the community. There were also floods with Major Disaster Declarations in 2016 and 2018, but these events did not illicit such widespread tax delinquency increases in the same communities as the first major flooding. After these flooding events, high-rate outliers emerge along the Waccamaw River and high-rate change clusters migrate higher up the Little Pee Dee, indicating new areas where the worst relative shocks have occurred in terms of lasting impact to housing in Horry County.

It is possible that the homes that were most likely to become financially abandoned due to a flooding event were mostly impacted by the events in 2015, therefore becoming unlikely to become delinquent again. This may potentially be because the property was fully abandoned and demolished, or because the home was purchased by a new owner who could invest into recovery. With the tax delinquency data provided by the county, it is impossible to say what happened to these cases, but locational context helps to focus any potential future investigation.

5.3 Caveats and Future Research

The idea that the areas near the water may be the most popular and sought-after areas to live in Horry County may confound some findings that may be true in counties where there is no such population growth and housing pressure. The unexpected lack of significance in the difference of tax delinquency for most years for flood prone and non-flood prone areas nevertheless calls into question how well the SFHA models exposure, and how well that exposure is communicated to homeowners and potential home buyers. The events in Horry County exceeded what was expected with a 1-in-100 Year event, which may confound this further.

The areas identified in this analysis, specifically those which experienced strong delinquency rate increases in 2016, undoubtedly raises questions about what social groups were the most likely to be affected by the floods, and how they were impacted. A closer look at these areas may reveal unique findings pertaining to what specific social vulnerabilities hide in coastal South Carolina related to housing recovery. In a county that is exploding in terms of population and housing, there may be unheard stories of hardship, uneven recovery, and lastly a changing face of local communities.

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