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GEOGRAPHICAL ANALYSIS OF OFFENDER VULNERABILITY: MODELING
COASTAL HAZARDS AND SOCIAL DISORGANIZATION IN SOUTHERN
MISSISSIPPI

by

Ashleigh Nicole Price

A Thesis
Submitted to the Graduate School,
the College of Arts and Sciences
and the School of Biological, Environmental, and Earth Sciences
at The University of Southern Mississippi
in Partial Fulfillment of the Requirements
for the Degree of Master of Science

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THE UNIVERSITY OF
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ABSTRACT

Hazards research continually examines how specific groups are affected by damaging events and how their unique sociodemographic characteristics contribute to variations in resilience and recovery. Studies have shown that underprivileged communities suffer more adversely and take longer to recover from hazard events. Probationers and parolees are uniquely disadvantaged regarding demographics and economic opportunity, both of which contribute to increased vulnerability and reduced resilience. Numerous legal restrictions and widespread discrimination towards former criminals means offenders are often relegated to underserved, criminogenic neighborhoods. Given such severe social and financial limitations, offenders have little capacity to prepare for or recover from disasters.

The primary objective of this project was to model offender residential patterns and examine the spatial relationship to physically vulnerable areas, local crime patterns, and offender support services in coastal Mississippi. A principal component analysis (PCA) consolidated explanatory measures from the criminology literature into the Social Disorganization Index (SDI). Hazus-MH 4.2.1 determined physical vulnerability for the 100-year return period. The results show that disorganized neighborhoods are not at significant risk from coastal or inland flooding and are moderately at-risk from hurricane winds. Comparison of the SDI to area crime patterns reveal there is a slightly elevated instance of criminal activity in disorganized neighborhoods. Offender support services are available throughout the region, although a lack of public transportation prevents offender access in some of the study area. The results of this study fill a gap in hazards research by investigating a previously overlooked, vulnerable population.

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LIST OF ABBREVIATIONS

<i>CTA</i>	Coast Transit Authority
<i>DEM</i>	Digital Elevation Model
<i>ESRI</i>	Environmental Systems Research Institute
<i>FDG</i>	Flood Depth Grid
<i>FEMA</i>	Federal Emergency Management Agency
<i>FFFM</i>	Families First for Mississippi
<i>FIS</i>	Flood Insurance Study
<i>FWS</i>	United States Fish and Wildlife Service
<i>GBS</i>	General Building Stock
<i>GPT</i>	Gulfport-Biloxi International Airport
<i>Hazus</i>	Hazus-MH 4.2.1
<i>HB 585</i>	Mississippi House Bill 585
<i>HI</i>	Herfindahl Index
<i>KAFB</i>	Kessler Airforce Base
<i>MARIS</i>	Mississippi Automated Resource Information System
<i>MGCCC</i>	Mississippi Gulf Coast Community College
<i>MDOC</i>	Mississippi Department of Corrections
<i>MGC</i>	Mississippi Geospatial Clearinghouse
<i>MPC</i>	Master Planned Community
<i>NCBC</i>	Naval Construction Battalion Center
<i>NED</i>	National Elevation Dataset
<i>PCA</i>	Principal Components Analysis

<i>PUD</i>	Planned Unit Development
<i>SWEL</i>	Stillwater Elevation(s)
<i>UCR</i>	Uniform Crime Reports
<i>USACE</i>	United States Army Corps of Engineers
<i>USGS</i>	United States Geological Survey

CHAPTER I – INTRODUCTION

Overview

The purpose of this research was to characterize the hazard vulnerability of the offender population in Hancock, Harrison, and Jackson County, Mississippi and examine whether this vulnerability could impact reentry outcomes. This thesis draws from social disorganization theory to relate neighborhood characteristics to the presence of offenders. The primary research objectives were to create a statistical model of offender residential patterns using socioeconomic indicators from the social disorganization literature, identify potentially hazardous areas with probabilistic hazard modeling, and understand the impact to reentry outcomes via the availability of offender support services and the relationship to neighborhood crime rates. This chapter discusses a need for this study in light of recent legislation and describes the sociodemographic characteristics of the offender population, followed by the research questions and expected outcomes.

Hazard Vulnerability in the Gulf Coast States

The United States Gulf of Mexico coastal region has experienced many of the nation's most devastating disasters in recent decades. During the Atlantic hurricane season, which runs from June through November, tropical systems routinely develop into severe storms that jeopardize public safety, infrastructure, and local economies across the region (Brusentsev and Vroman 2017; Groen, Kutzbach, and Polivka 2017). Significant hydro-meteorological events are a natural part of coastal life, yet severe weather continues to disproportionately affect marginalized populations of the Gulf Coast.

A growing body of literature shows that poor, minority communities are at a higher risk from hazards, are more adversely affected by hazard impacts, and take longer

to recover from hazard events (Adeola and Picou 2012; Prasad 2012). The Gulf Coast states are home to large minority populations and have poverty levels above the national average. This is especially true for coastal Mississippi, where substantial numbers of impoverished people, many of whom have limited capacity for mitigation and recovery, reside in hazardous areas (Burton 2010; Yoon 2012; Logan and Xu 2015).

Probation and Parole

In the United States, over 4.5 million people are currently on supervised parole or probation (Kaeble 2018). Of the 2 million people currently in prisons or jails, nearly all of them will be released to community supervision sometime in the future. These individuals typically come from reduced socioeconomic backgrounds, have limited educational attainment, and suffer from societal ostracization (Hughes, Wilson, and Beck 2001; Petersilia 2003; Pettit and Western 2004; Clear 2007). Mississippi has the third highest incarceration rate in the nation and is one of the few states to report an annual increase in prison admissions in recent years (Carson 2018).

The state prison population has grown steadily, in part due to parolees and probationers returning to prison for technical violations. In 2014, Mississippi House Bill 585 (HB 585) took effect for new offenses. HB 585 aims to clarify sentencing guidelines, reduce reincarceration for technical violations, and lower the prison population (MDOC 2013, 2014). Given that most offenders are supervised following release, prison depopulation increases community corrections caseloads (Figure 1). MDOC currently supervises over 20,000 inmates and 32,000 parolees and probationers (MDOC 2018).

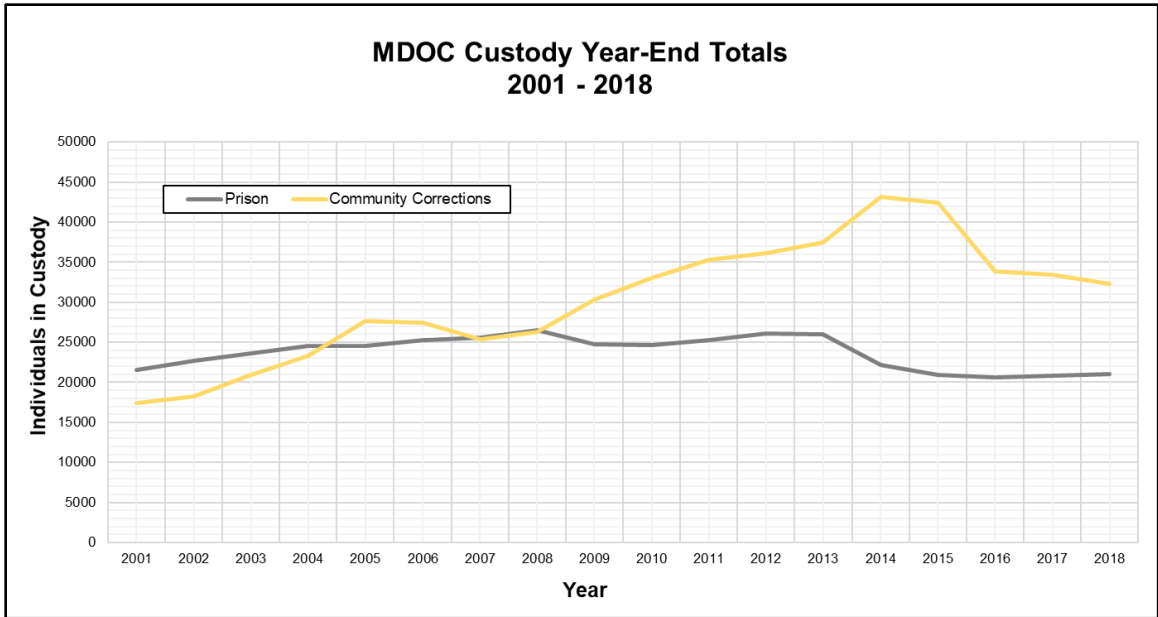


Figure 1. Mississippi Offenders by Custody Level, 2001-2018

The year-end MDOC custody totals show decreasing prison populations and increasing community supervision caseloads (MDOC 2001-2018).

The Offender Population

Offenders (probationers and parolees) are uniquely disadvantaged regarding demographics, employment options, and housing opportunities, all of which can contribute to heightened social vulnerability and reduced resilience (Petersilia 2003; Mears and Cochran 2015). The offender population is largely African American, male, and between the ages of 18 and 39 (Hughes, Wilson, and Beck 2001; Pettit and Western 2004; Carson 2018). In fact, most offenders are ethnic minorities. African Americans are convicted at rates 5 times higher and sentenced to longer sentences than their white counterparts (Hughes, Wilson, and Beck 2001; Carson 2018; Zeng 2018). MDOC reports show most Mississippi parolees and probationers are African American, male, and convicted of drug or other non-violent offenses (MDOC 2018).

Offenders have a unique set of legal and social constraints. Many released inmates have few prospects or resources and return to low-income neighborhoods, where high criminal activity occurs, facing few opportunities for employment (Clear 2007; Hipp, Petersilia, and Turner 2010; EmpowerMS.org 2019). Most incarcerated individuals did not graduate from high school (Harlow 2003; Pettit and Western 2004; Arum and Lafree 2008), which tends to limit their legal employment options to low-wage jobs. Employers are reluctant to hire individuals with criminal records and in many cases can legally refuse to hire felons (Pager 2003; Petersilia 2003). In fact, probationers and parolees are subject to numerous legal restrictions. Drug convictions can result in an offender's permanent exclusion from public housing, federal student aid (FMS 2015), and welfare benefits (The Sentencing Project 2013). Many convictions also require extensive financial penalties, participation in treatment programs, and driver's license restrictions (Petersilia 2003), leaving offenders to rely on others for housing and transportation.

Offenders have limited personal support, and relationships with friends and family members can deteriorate over the course of prison terms. Family members may be unwilling or unable to support offenders upon release (Hairston 2002; Petersilia 2003). Offenders also face social stigmas, as evidenced in the vast lexicon of pejorative slang (Hill and Banks 2018) and the lack of person-first descriptors for those with a criminal record (Denver, Pickett, and Bushway 2017). Such widespread discrimination against former criminals means offenders are relegated to the least desirable residential areas. These neighborhoods are often underdeveloped, limiting employment options and access to support services. In short, offenders are a unique segment of the population that is

subject to reduced economic opportunity, limited housing options, community ostracization, and routine scrutiny from law enforcement.

Research Problem

Hazards research is increasingly focused on ways in which specific demographic groups are affected by damaging events and how this contributes to variations in resilience and recovery at different spatial scales (Chakraborty, Tobin, and Montz 2005; Wood, Burton, and Cutter 2010; Montz, Tobin, and Hagelman 2017). The Gulf Coast states are home to large numbers of minorities, immigrants, elderly individuals, and migrant workers. Regarding disaster recovery, these groups share several significant factors with offenders, including mobility limitations, reduced socioeconomic status, and special risk communication needs. Studies have illustrated how these disadvantaged individuals are adversely affected during hazard events, as well as their unique impediments to resilience (Carter-Pokras et al. 2007; Rosenkoetter et al. 2007; Gares and Montz 2014). This research draws from these studies to characterize the vulnerability and resilience of the offender population to hazards.

Objectives and Research Questions

The purpose of this research is to measure the vulnerability and resilience of the offender population of the three counties of the Mississippi Gulf Coast. In particular, this thesis will analyze the spatial relationships among the offender population, their support services, local crime rates, and physically hazardous areas of the Gulf Coast. This project is based on the following research questions: (1) How does an impending disaster alter routine community corrections operations in Hancock, Harrison, and Jackson counties? (2) Where are the residential concentrations of supervised offenders in the Gulf Coast

counties of Mississippi? (3) Where are the most physically vulnerable areas regarding tropical cyclone activity? (4) Where are offender support services? (5) What are the spatial relationships among offender neighborhoods, physically vulnerable areas, support services, and local crime patterns.?

Expected Outcomes

This thesis will advance geographical hazards research by examining the vulnerability of a previously overlooked population and by designing a methodology applicable to other study areas. This study will contribute to the safety of marginalized populations and will shed light on how hazard vulnerability may relate to reentry outcomes. The results will be useful to emergency management and community corrections operations by characterizing the unique vulnerability of the supervised offender population.

CHAPTER II – REVIEW OF RELATED LITERATURE

Overview

This chapter first describes the concepts of vulnerability and resilience and provides a review of geographical studies examining marginalized groups, followed by a discussion of vulnerability in the offender population. Second, this chapter presents a review of the criminology literature informing the study of offender residential patterns. The chapter summary discusses the gap in literature that confirms a need for this research.

Vulnerability and Resilience

Disaster resilience and vulnerability serve as dual theoretical frameworks in hazards research. Their respective meanings vary across the literature, reflecting a diversity of perspectives and methodologies. In the broadest sense, *vulnerability* indicates the likelihood of being harmed or suffering loss from a hazard event. Vulnerability describes risk in the social, physical, and built environments from the perspective of underlying disaster risk drivers (Manyena 2006; Faas 2016; UNISDR 2017). Reduced socioeconomic conditions, biased development, infrastructure susceptibility, and the frequency or severity of an event all contribute to heightened vulnerability and variations in disaster outcomes across populations or within the same population. This research defines vulnerability simply as the risk of adverse effects from hazards.

Disaster resilience describes the ability to withstand a hazard and to recover afterwards. It focuses on the inherent coping capacity of an individual or a system and their post-event actions to return to normal. The term describes preemptive measures to aid recovery and implies a continuation of pre-event conditions (Manyena 2006; Faas

2016). For emergency management, being disaster resilient means developing emergency plans that increase a population's ability to respond to and recover from a hazard with minimal outside assistance (Haddow, Bullock, and Coppola 2014). This research uses disaster resilience to describe a group's capacity to mitigate, withstand, and recover from a hazard event.

While vulnerability and resilience are often represented as contrasting each other in the literature, they are not dichotomous. Increasing resilience does not imply a reduction in vulnerability. Human vulnerability describes the risk to personal safety and the post-disaster impacts to public health. Physical vulnerability is a function of proximity to a hazard and the severity or frequency of an event. Vulnerability in the built environment is the potential risk to residential property, utility and transportation networks, and government, economic, and cultural infrastructure (Borden et al. 2007). Social vulnerability describes how socioeconomic and demographic characteristics contribute negatively to disaster mitigation and recovery (Cutter, Boruff, and Shirley 2003; Manyena 2006).

Quantitative vulnerability research focuses on the development of indices and models that rely upon a wide range of socio-demographic, economic, and environmental variables. Deductive approaches use the established body of literature to develop standardized indices for comparing the vulnerability of geographic locations or social classes (Cutter, Mitchell, and Scott 2000; Wu, Yarnal, and Fisher 2002; Chakraborty, Tobin, and Montz 2005; Prasad 2012; Remo, Pinter, and Mahgoub 2016; Oulahan et al. 2017). Inductive methods in vulnerability research use factor analysis to objectively determine contributors to variance within a study area. The result is a representation of

the overall vulnerability of a place (Cutter, Boruff, and Shirley 2003; Borden et al. 2007; Yoon 2012; Remo, Pinter, and Mahgoub 2016). Comparison among indices shows common variables among at-risk communities.

Race, poverty, and infrastructure density are the largest contributors to hazard vulnerability (Prasad 2012; Yoon 2012). Recent geospatial research shows an increasing number of minorities and low-income individuals live in the most physically vulnerable areas (Chakraborty 2009; Burton 2010; Prasad 2012). For the Gulf Coast states, hydro-meteorological hazards create physical vulnerability, while infrastructure value and residential density controls vulnerability in the built environment. Social vulnerability results from reduced socioeconomic status among large portions of the population. Additionally, longitudinal trends show these vulnerable populations are moving from coastal communities into high risk areas (Logan and Xu 2015). In coastal Mississippi, routine tropical cyclone activity, large minority populations, high population density, and the presence of oil and gas operations, and commercial ports increase overall place vulnerability (PEER 2006; Borden et al. 2007; Yoon 2012).

Qualitative research via case studies provides additional understanding of a group's unique vulnerabilities. Marginalized populations become disproportionately at-risk to hazards through multi-dimensional processes such as biased economic growth and development, community ostracization, and social stigmas. Historically produced inequalities also result in a lack of resources such as limited employment, transportation access, and housing options (Peterson and Krivo 2010), thereby increasing vulnerability (Bolin, Grineski, and Collins 2005; Ueland and Warf 2006; Logan and Xu 2015; Faas 2016).

A number of case studies have illustrated how marginalized groups can be at greater risk during hazards than neighboring populations. Gares and Montz (2014) captured the unique vulnerabilities of migrant workers. Reduced socioeconomic status, proximity to multiple hazards, and distrust towards authority figures means these individuals are disproportionately exposed to risk on a routine basis and in times of disaster (Gares and Montz 2014). Racially biased development has contributed to creating adverse conditions for African Americans and other minority groups, as poor neighborhoods are often concentrated in low-lying, flood prone areas (Ueland and Warf 2006; Sayers, Penning-Rowsell, and Horritt 2018) or near existing environmental hazards (Bolin, Grineski, and Collins 2005; Chakraborty 2009; Grineski et al. 2012; McDowell 2013; Collins et al. 2015; Pulido 2015). Low-income residents might also live in structurally vulnerable housing and lack insurance and mitigation capabilities (Burton 2010; Walker and Burningham 2011). Access and functional needs contribute to risk in both routine and hazardous conditions. The elderly (Rosenkoetter et al. 2007), hearing impaired individuals (Wood and Weisman 2003), those with limited English proficiency (Carter-Pokras et al. 2007), rural residents (Prelog and Miller 2013; Cole and Murphy 2014), and the homeless (Settembrino 2017) have all been identified as groups with exceptional vulnerabilities.

Large proportions of vulnerable groups reduce disaster resilience in a community. Social capital provides both routine support and opportunities for disaster resilience. Individuals in marginalized communities often boost their social capital through religious and civic organizations, shared cultural heritage, and kinship. Strong social ties via family and friends can provide physical capital such as housing and transportation. Weak social ties can offer networking benefits like access to employment opportunities (Murphy 2007).

High social capital is linked to better resilience and recovery outcomes for both individuals and communities. Friends and family are a primary source for emergency information (Cochran and Kar 2016). Individuals look to their social networks when deciding to undertake mitigation measures (Wood et al. 2012; Wallace, Keys-Mathews, and Hill 2015) or respond to evacuation orders. Social capital determines collective efficacy in that close-knit groups share responsibility for disaster preparation, response, and recovery. Those with strong social networks report fewer post-disaster health issues, lower levels of post-traumatic stress disorder (Adeola and Picou 2012, 2014), and improved post-traumatic growth (Lee et al. 2018), even among those experiencing residential displacement (Tsuchiya et al. 2017).

Offender Vulnerability

Vulnerability among offenders results from limited housing and employment options and from reduced socioeconomic status. Mobility restrictions, including travel limitations and driver's license prohibitions can constrain where offenders live and work. A criminal record can be more important than prior work experience and many employers are hesitant to hire offenders, even for entry-level positions (Pager 2003).

Supervision conditions can require individuals to seek employment, highlighting unique risks in times of disaster. Offender employment opportunities are often limited to low-skill, low-wage jobs, such as those in retail services and manual labor (Petersilia 2003; Mears and Cochran 2015). Following Hurricane Katrina, the tourism industry saw an immediate spike in unemployed leisure/accommodations workers due to the interruption in business and the destruction of tourism and leisure facilities (Groen, Kutzbach, and Polivka 2017). Of those that remained employed, many saw a reduction in weekly wages (Vigdor 2008) and numerous manual laborers were subjected to unsafe working environments (Delp, Podolsky, and Aguilar 2009). Given their limited job prospects, offenders are particularly vulnerable to such hazard events.

There is little opportunity for offenders to advance professional careers. The federal government imposes a lifetime ban on all forms of student aid for drug offenders, eliminating college opportunities for over 40% of Mississippi parolees and probationers (Hattery and Smith 2010; MDOC 2018). Depending on the nature of their convictions, offenders might also be banned from public housing. State-level sanctions can impose additional penalties and limit offender access to public assistance and professional licensure. The state of Mississippi imposes no fewer than 1,700 such penalties, making it the most exclusionary state in the nation (Petersilia 2003; CSG Justice Center 2019).

Much of the literature regarding the offender population examines the individual likelihood and external influences on recidivism rates. Within 5 years of release, over 75% of former inmates will commit another crime or otherwise violate parole (Petersilia 2003; Mears and Cochran 2015). Recidivism rates are higher among males, African Americans, and those with multiple prior convictions (Kubrin and Stewart 2006;

Wehrman 2010). Recidivism is also linked to neighborhood characteristics, including socioeconomic disadvantage (Kubrin and Stewart 2006; Hipp, Petersilia, and Turner 2010), the availability of reentry support services (Hipp et al. 2011), the presence of community organizations (Wallace 2015), and living in proximity to other known offenders (Harding, Morenoff, and Herbert 2013; Stahler et al. 2013).

Offenders tend to return to familiar communities, meaning former prisoners are spatially focused in economically disadvantaged neighborhoods (Kirk 2009, 2012; Brantingham and Brantingham 2010b; Hipp, Petersilia, and Turner 2010), and such neighborhoods are often in the most physically hazardous locations (Logan and Xu 2015). Thus, offenders might have few options other than to reside in areas that are vulnerable to hazards and conducive to criminal activity. This suggests reducing hazard vulnerability could also impact reentry outcomes. Following Hurricane Katrina, residential displacement was shown to lower re-offense rates by removing parolees from criminogenic neighborhoods (Kirk 2009). In this way, situations representing resilience in the mainstream population (e.g. residential stability) could put offenders at risk in times of disaster and could be detrimental to prisoner reentry.

Successful reentry is more likely for individuals utilizing community services, including employment agencies, life skills and workplace training, and treatment programs. These services help maintain the conditions of release while serving as advocacy groups and social capital for the formerly incarcerated (Hipp, Petersilia, and Turner 2010). Similarly, community supervision conditions require offenders to routinely visit local probation and parole offices. In some ways, the conditions of release can hinder an offender's access to support services and their supervision officer. Shelters,

transitional centers, and affordable housing are often located in underdeveloped neighborhoods. These areas are unlikely to have public transportation or to accommodate pedestrian travel. Additionally, many convictions include driver's license restrictions and supervision conditions can limit offender travel to their county of residence. The result is offenders living far from the necessary locations, with little means to travel (Petersilia 2003; Hattery and Smith 2010).

Friends and family members are the primary source of housing, transportation, and social capital for offenders. Maintaining these social ties through prison visits contributes to improved inmate behavior and positive reentry outcomes (Warr 1998; Hairston 2002). Incarceration, however, is deleterious to personal relationships as there are significant barriers to visitation (Clear 2007). Corrections facilities are typically located in remote areas. Disadvantaged families may lack the resources to travel overnight, make childcare arrangements, or take time off work (Cochran et al. 2016). Minority offenders tend to be incarcerated further from home and are generally less likely to receive visitors than white offenders (Cochran, Mears, and Bales 2017). At the end of their sentence, many inmates are left with no personal support. According to the Mississippi Offender Reentry Experience (MORE), as many as 700 parolees remain incarcerated every month because they cannot secure housing for their release (MORE 2019).

Routine Activity Theory

Routine activity theory frames criminal activity as the result of situational, place based-opportunity. Crimes occur where there is a motivated offender, a suitable target, and absent capable guardians. The offender may actively choose to seek out a target or

identify a suitable opportunity during the course of non-criminal behavior (Cohen and Felson 1979; Brantingham and Brantingham 2010a). Routine activity occurs near anchor points, where offenders live, work, or otherwise have a familiar presence (Rossmo 2000; Bernasco 2010). For homeless or residentially transient offenders, the anchor point may be a close friend or family member's home, public space, or local establishment (Rossmo 2000; Brantingham and Brantingham 2010b). Travel sanctions and a lack of vehicle access further limit offender movement.

Social barriers also constrain the activity space. Offenders are less likely to operate in neighborhoods that are racially or ethnically different from their own (Reynald et al. 2008). Offenders feel more conspicuous and unable to avoid detection in outlying communities (Wright and Decker 1997; Murray et al. 2013). Reynald and others (2008) described 8 years of urban crime trips in 94 neighborhoods of The Hague, Netherlands, a city well known for its geographic segregation of poor and minority communities. The results showed offenders tended to commit crimes in their own neighborhoods and nearby areas most socioeconomically and ethnically similar to their own (Reynald et al. 2008). Bernasco and Block (2009) showed that African American offenders are more likely to commit robberies in areas where the majority of the population is also African American (Bernasco and Block 2009). Racially motivated gang activity also puts offenders at considerable risk in rival territory (Tita, Cohen, and Engberg 2005). The social limitations to activity space are especially pronounced in urban spaces, where racial and social neighborhood characteristics, and thus criminal opportunities, are concentrated in small geographic areas (Wehrman 2010).

Crime pattern research examines criminogenic land use. Generally, non-residential land use contains locations for routine activity where offenders might find suitable targets (Browning et al. 2010). Crime generators are public spaces drawing large numbers of people during legitimate business hours, some of which are motivated offenders (Groff and Lockwood 2014). Shopping centers (Wilcox et al. 2004), parks (Boessen and Hipp 2018), schools (Bernasco and Block 2009), and transit stations (van Wilsem 2009; Zhang 2016) are often cited as crime generators (Hipp and Kubrin 2016). Crime attractors are locations with a high instance of susceptible targets, typically carrying cash. The presence of illicit activity, like drug dealing or prostitution, creates attractive robbery targets as victims are both carrying cash and unlikely to report the incident (Wright and Decker 1997). Legitimate businesses also serve as crime attractors. Casinos bring together tourists unfamiliar with the area, local offenders, and open displays of money (Stitt, Nichols, and Giacopassi 2003). Other crime attractors include ATMs (Deakin et al. 2007), pawn shops, (Bernasco and Block 2011), and fringe banks (Hipp and Kubrin 2016).

Due to zoning regulations, the types of business that serve as crime attractors/generators are typically located in commercial areas. A 2009 study by Stucky and Ottensmann found violent crime increases with commercial density (Stucky and Ottensmann 2009). Anderson (2013) found that mixed-use zoning indicated higher crime when compared to exclusively residential neighborhoods (Anderson et al. 2013). Impoverished areas tend to have larger proportions of commercial land use (Small and McDermott 2006) than more affluent areas, meaning criminal opportunity is concentrated

in disadvantaged areas. Given offenders' reduced socioeconomic status, they are likely to live near numerous criminal opportunities.

Proximity to crime research examines the distance offenders travel to criminal opportunities. Geoprofiling is an investigative spatial analysis technique used to locate offenders. When multiple incidents are attributed to a single offender, or cluster of offenders, the spatial distribution of crime scenes can lead to probable offender anchor points (Rossmo 2012). Inversely, crime trip studies examine the distance known offenders have traveled to find suitable targets. Using the offender's last known address and the incident location, geoprofiling and crime trip studies show common results across offense type and severity.

Kent, Leitner, and Curtis (2006) analyzed several years of homicide data to calibrate a geoprofile of the Baton Rouge serial killer. The study found murder victims were targeted within 12 miles of the offender's residence (Kent, Leitner, and Curtis 2006). Groff and McEwen (2006) conducted a similar study over the Washington, D.C. metro area. Homicides occurred an average of less than 3 miles from the offenders' homes (Groff and McEwen 2006). Bernasco (2010) showed thefts from vehicles tend to occur in the offender's own zip code (Bernasco 2010). Integrating crime pattern research with routine activity theory reveals offenders often choose nearby, accessible targets.

Collective Efficacy

Collective efficacy theory describes how a sense of shared responsibility motivates citizens to address criminal behavior in their communities. Effective communities have strong social ties that include an established set of values and cultural norms. Social networks often exist within cultural, ethnic, or class barriers, meaning the

most cohesive groups tend to be the most socioeconomically and demographically homogeneous. Similarly, large proportions of long-term residents and high home ownership rates indicate a vested interest in the neighborhood. This local interconnectedness sets the standard for acceptable behavior, creating informal social control over crime. Residents feel justified in reporting crimes and intervening when delinquent youth gather in public. In effective communities, residents, rather than law enforcement, are the primary capable guardians (Clarke and Felson 2008).

Social Disorganization

Social disorganization theory explains how neighborhood characteristics can reduce collective efficacy and contribute to crime. Concentrated disadvantage, residential instability, and ethnic heterogeneity can reduce capable guardianship by promoting anonymity among residents. In this way, disorganized communities lack the collective efficacy to prevent crime.

Concentrated disadvantage describes resource deprivation in extremely poor urban communities. These neighborhoods are impoverished (Harding, Morenoff, and Herbert 2013), densely populated (Stucky and Ottensmann 2009), and have large minority populations (Sampson and Raudenbush 2004; Tita, Cohen, and Engberg 2005). These areas generally have low high school completion rates, high unemployment (Baumer et al. 2003; Hipp, Petersilia, and Turner 2010), and a prevalence of single-parent households (Krivo and Peterson 1996; Bouffard and Muftic 2006) receiving public assistance (Demotto and Davies 2006; Wehrman 2010).

Disadvantaged families are unlikely to own a home and renters move more often than homeowners. Thus, disorganized communities have many short-term residents with

few social ties. Criminal activity may also contribute to residential mobility in that residents of criminogenic neighborhoods are likely to become victims themselves (Nieuwbeerta et al. 2008; Browning et al. 2010).

Disorganized communities are racially and ethnically heterogeneous, meaning there is little cultural connectedness and among groups, as social ties are unlikely to cross socioeconomic and racial barriers. Poor, minority communities also tend to be spatially isolated from more affluent, white populations (Sampson, Morenoff, and Gannon-Rowley 2002; Ueland and Warf 2006; Peterson and Krivo 2010). Social disorganization theory suggests that this spatial and social distance creates distrust and indifference among neighbors. Residents become disinvested with their neighborhoods, reducing community engagement and the productive use of public spaces.

Citizens of all races assume the presence of minority populations equate with high crime, although whites tend to be more biased in that regard. In racially diverse neighborhoods, white residents are likely to believe the area is criminogenic, regardless of actual crime rates. Sampson and Raudenbush (2004) showed that this *perceived* disorder promotes criminal activity. Residents can become wary of public spaces, reducing capable guardianship over street crimes (Skogan 1992; Sampson and Raudenbush 2004; Clear 2007).

Many social scientists have discussed how criminal activity results from a prevalence of unsupervised adolescents with negative peer influences (Warr 1998; Mennis et al. 2011). In neighborhoods with a high occurrence of single-parent households, youth may be left to their own devices while parents work (Wehrman 2010). Without positive role models, groups of adolescents are likely to engage in unproductive

and illegal behavior (Howell 1998). In urban neighborhoods, this manifests itself in groups of teens gathering on street corners and engaging in street crimes (Putnam 2000). In other cases, adolescents gather at the homes of inattentive or lenient parents. These groups of delinquent youth are unlikely to finish high school, obtain legitimate employment, and may in turn transition to adults who commit more serious offenses (Pettit and Western 2004; Tita, Cohen, and Engberg 2005).

The stigma surrounding disadvantage and crime impacts the entire community. Businesses find these neighborhoods undesirable, limiting community development and nearby job opportunities (Clear 2007). Offenders who do find employment face scrutiny in the hiring process (Pager 2003) and feel they will be unduly terminated (Clear 2007). Employers are generally disinclined to hire residents from criminogenic neighborhoods, regardless of an individual's criminal history (Anderson 1999; Wehrman 2010). The dearth of economic opportunity tends to further isolate disorganized communities from traditional society, altering social norms (Krivo and Peterson 1996). Met with few legitimate employment options, illicit activity provides a socially acceptable, often lucrative income (Anderson 1999; Wang and Minor 2002).

Summary

An extensive body of literature informs the geography of crime. Social disorganization theory explains how structural neighborhoods characteristics contribute to criminogenesis. Routine activity theory describes the basic elements necessary for a crime to occur: a suitable target, motivated offender, and a lack of capable guardianship. Crime pattern research examines how land use creates criminal opportunity, while proximity to crime and geoprofiling studies show offenders tend to commit crimes in

familiar areas. This research integrates these frameworks to model offender residential patterns and highlight the unique vulnerability of the offender population.

Offenders are a highly disadvantaged group and tend to live in underprivileged, marginalized, criminogenic areas. Given such severe social and economic limitations, offenders have little capacity to prepare for or recover from disasters. Additionally, the offender population is under-represented in the hazards literature. There is currently little published research on the conditions of release and the socioeconomic status of offenders, or how local hazard conditions alter community corrections operations. It is not understood how community supervision standards affect hazard vulnerability, whether support services improve disaster resilience, or if the presence of the offenders pose additional risks to public safety during a disaster. Most significantly, there has been little examination of the spatial relationships among offender residences, physically hazardous areas, support services, and area crime patterns.

CHAPTER III - STUDY AREA

Overview

This study examined the three counties of the Mississippi Gulf Coast: Hancock, Harrison, and Jackson. The area was chosen for its proximity to coastal hazards, high socioeconomic diversity, and large community corrections presence. During the Atlantic hurricane season, the region is routinely exposed to tropical cyclone activity. With the prospect of climate change, the frequency and intensity of severe weather is expected to increase in the coming decades. The presence of oil and gas infrastructure can produce anthropogenic hazards, as evidenced by the 2010 Deepwater Horizon Oil Spill (Lazarus 2016). Above average poverty levels, large minority populations, and high population density contribute to social vulnerability and concentrated disadvantage. Additionally, a large proportion of Mississippi's supervised offenders live in the coastal counties.

Population Characteristics

Hancock, Harrison, and Jackson counties stretch from west to east along the Mississippi Gulf Coast (Figure 2). Despite the impacts of Hurricane Katrina, the Gulf Coast population has grown steadily in recent years (Table 1). The 2010 US Census recorded the tri-county population as 370,702 and it was estimated at 385,448 in 2016. The coastal cities are densely settled, while the area north of I-10 is exclusively small towns and unincorporated places. Population density is low (< 50 people per sq. mile) to the north and exceeds 3,000 people per sq. mile in parts of Gulfport, Biloxi, Moss Point, and Pascagoula (Figure 3).



Figure 2. Study Area: Hancock, Harrison, and Jackson County, Mississippi

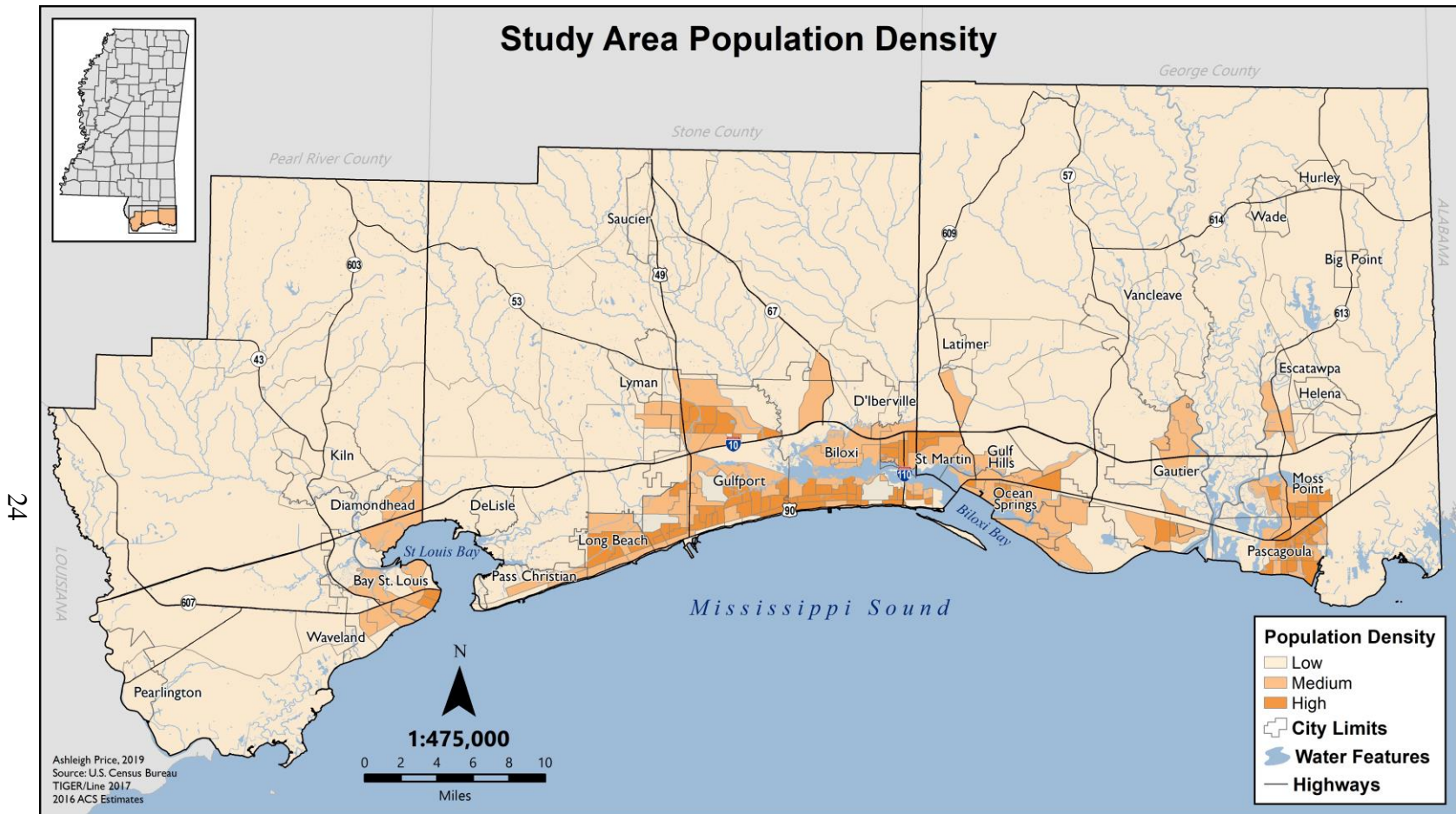


Figure 3. Study Area Population Density

Block-group population density, quantile classification (US Census Bureau, 2016 ACS 5-year estimates).

Table 1

Study Area Population Growth

	Hancock	Harrison	Jackson
2000 Census	42,967	189,601	131,420
2007 ACS Estimates	41,567	181,764	130,863
2010 Census	43,929	187,105	139,668
2016 ACS Estimates	46,028	198,570	140,850
Percent Population Growth 2000-2016	7.12%	4.73%	7.18%

Study area population growth 2000-2016. Percentages are based on county population (US Census Bureau, 2000/2010 Census, 2007/2016 ACS 5-year estimates).

The Mississippi coastal counties are culturally and socioeconomically diverse. Compared to state averages, residents tend to be wealthier, more educated, and less likely to be an ethnic minority (Table 2). Three-quarters of the population is Caucasian, median income is high, and overall unemployment is lower than that of Mississippi as a whole. Social vulnerability, however, is prevalent in coastal Mississippi. Finer-scale analysis highlights poor, minority neighborhoods throughout the tri-county area, many of which are still recovering from Hurricane Katrina. Household poverty rates exceed the state average in much of the study area (Figure 4) and 13.4% of the tri-county population does not have a high school diploma. There are significant Hispanic and Vietnamese immigrant populations, many of which suffer from a language barrier (Cochran and Kar 2016). While urban growth has continued post-Katrina, approximately 12% of residential properties are currently vacant.

Table 2

Study Area Population Characteristics

	Hancock	Harrison	Jackson	Mississippi
Caucasian	40,096 (87.1%)	136,866 (68.9%)	101,277 (71.9%)	59.0%
African American	4,407 (9.6%)	47,258 (23.8%)	30,621 (21.7%)	37.5%
Other	703 (1.5%)	6,637 (3.3%)	3,582 (2.5%)	2.3%
Hispanic	1,694 (3.7%)	10,569 (5.3%)	7,756 (5.5%)	2.9%
Poverty	17.4%	19.3%	16.0%	22.3%
Unemployment	8.8%	9.6%	8.7%	9.6%
HS Completion	84.3%	86.3%	87.7%	83%
Vacant Residential Property	10.7%	11.7%	15.02%	11.8%

Selected population characteristics for Hancock, Harrison, and Jackson Counties and the State of Mississippi. Percentages are based on county population (US Census Bureau, 2016 ACS 5-year estimates).

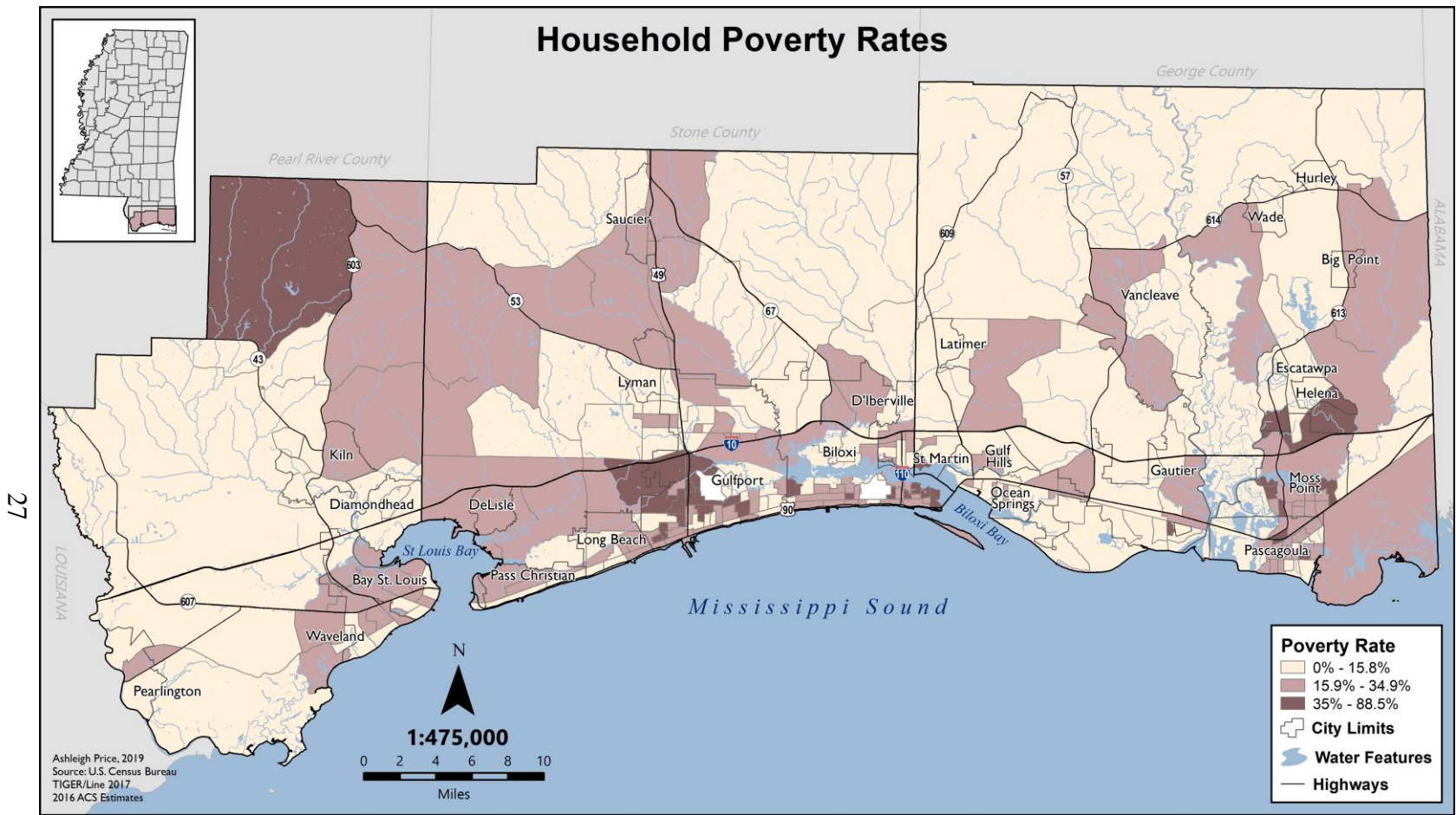


Figure 4. Household Poverty Rates

Block-group household poverty rates, Jenks classification (US Census Bureau, 2016 ACS 5-year estimates).

Physiographic Characteristics

The inland tri-county area encompasses 1,781 square miles, with approximately 44 miles of coastal shoreline (NOAA 2008). The coastline borders Mississippi Sound, which extends seaward to the barrier islands. There are numerous bays, bayous, estuaries, and marshes along the shore and wildlife preservation areas exist throughout the study area. The inland section of the region is largely agricultural or forested (Figure 5). Northern Hancock County consists of small farm communities and public 16th section lands leased for hunting and agriculture. DeSoto National Forest comprises much of northern Harrison County east of Highway 49. In northwestern Jackson County, there are extensive marshes and swamps surrounding the Pascagoula and Escatawpa Rivers.

Coastal Mississippi features extensive stream networks and much of it lies within the 100-year floodplain (Figure 6). The largest drainage system in the region is the Pearl River of western Hancock County. During heavy precipitation events, the Pearl River brings flooding to marshes near the coast and along the Louisiana border (FEMA 2009a). In western Harrison County, the Wolf River flows southward to St. Louis Bay. The Little Biloxi River converges with the Biloxi River and drains into the Back Bay of Biloxi, along with the Tchoutacabouffa River. The marshes and lakes of the region, especially near the coasts, are subject to flooding during both heavy rainfall and coastal surge events (FEMA 2009c). In Jackson County, the primary riverine flood sources are the Pascagoula River and its tributaries Black Creek and the Escatawpa River (FEMA 2009d). The primary coastal flood sources are St. Louis Bay, Biloxi Bay, the Back Bay of Biloxi, and the bayous and marshes near the sound in Jackson and Hancock Counties (FEMA 2017a, 2017b).

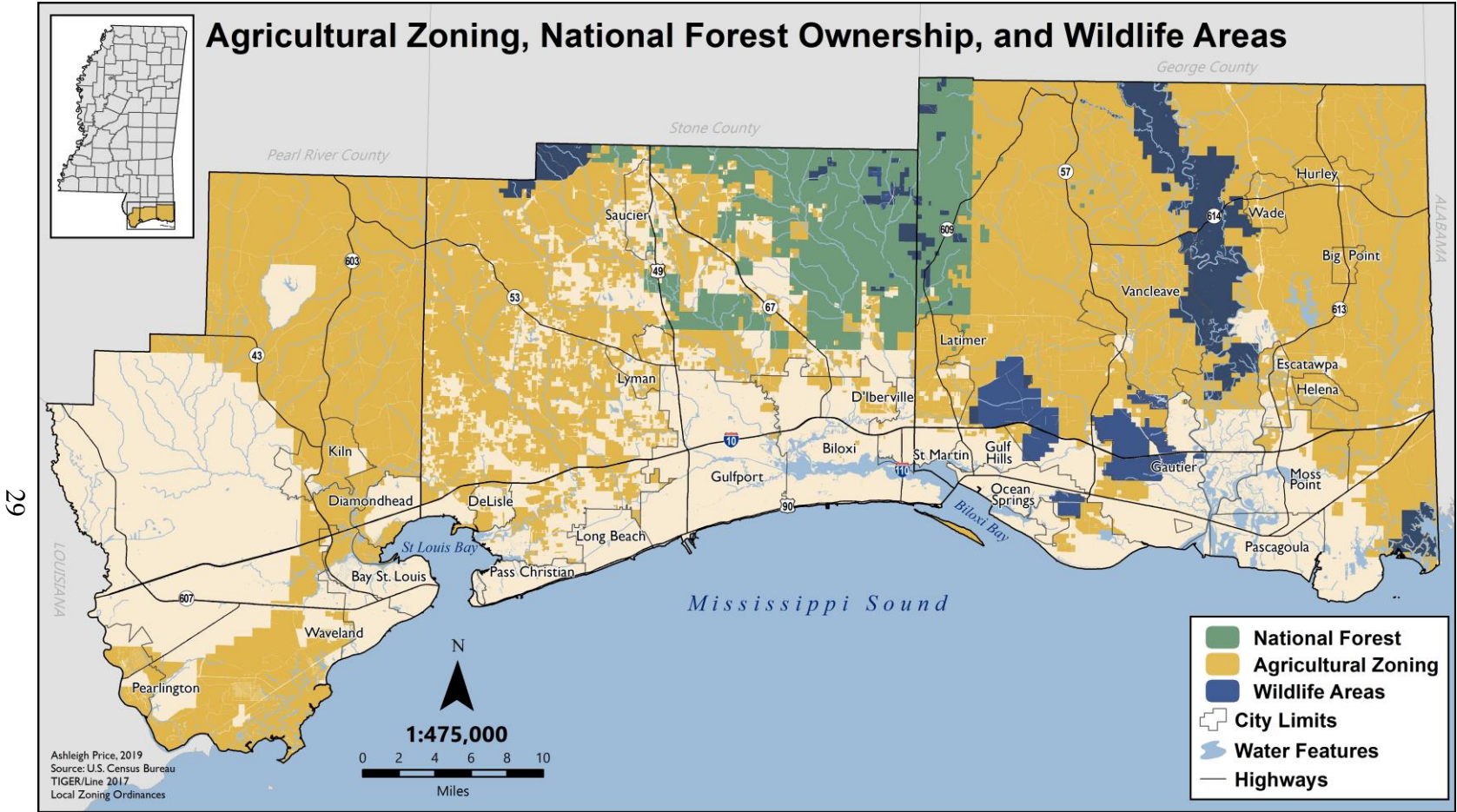


Figure 5. Agricultural Zoning, National Forest, and Wildlife Preservation Areas

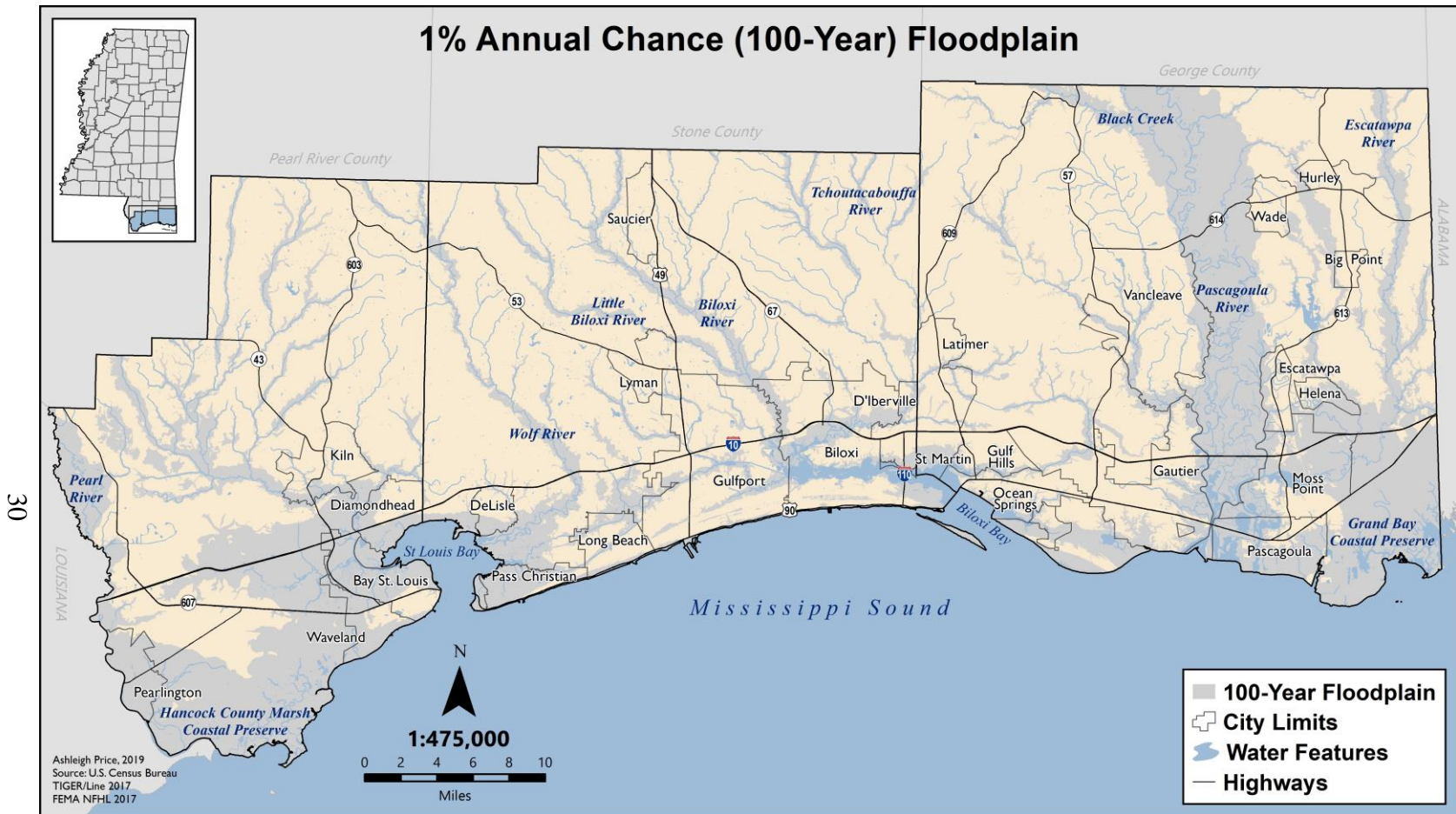


Figure 6. 1% Annual Chance (100-Year) Floodplain

Spatial extent of the 100-year floodplain with selected flood sources labeled (FEMA 2017)

Hurricane Activity

Coastal Mississippi is routinely exposed to tropical cyclones. During the Atlantic Hurricane season, the entire area is at risk of storm surge inundation, inland flooding, and damaging winds. Heavy rains associated with tropical cyclone landfall produce flash flooding upstream in the inland areas of coastal watersheds, while areas outside of the floodplain remain at risk of wind damage. The Mississippi Sound covers a shallow sloping near-coastal water body, increasing potential storm tide, while the concave shape of the coastline shape intensifies storm surge in bays along the coast. This effect was so pronounced during Hurricane Katrina, that most tide sensors malfunctioned, ceasing data collection prior to landfall (NOAA 2005).

In 2005, Hurricane Katrina made landfall as a category 3 hurricane near the Louisiana border. Prior to landfall, Katrina produced substantial wave setup in Mississippi Sound. Water levels were 3 and 7 feet above the predicted levels in Biloxi and Waveland respectively. In Ocean Springs, water levels were over 11 feet above the predicted elevation. The orientation of storm track brought northward winds to the Mississippi coast, pushing the storm surge a significant distance inland (NOAA 2005). FEMA reports estimate high water marks reached 28 feet around St. Louis Bay and as high as 22 feet more than 10 miles inland in Jackson County. As a direct result of storm surge, 238 Mississippi residents were killed (Robertson 2015), while countless others were displaced. In total, over 69,000 homes were damaged or destroyed (DHS 2006).

Social Vulnerability in Coastal Mississippi

Within the coastal cities of Mississippi, there are substantial numbers of impoverished and minority residents and some of them live in the path of coastal hazards. There are distinct geographic demarcations between poor, minority areas and more affluent neighborhoods in coastal Mississippi. Several block groups are home to large proportions of minorities, and these areas are situated near flood sources and around non-residential zoning. The Vietnamese immigrant population is concentrated in communities near the coast and along Biloxi Bay (Figure 7). There are small, but growing Hispanic populations throughout the study area (Figure 8). In central Jackson County, large numbers of African Americans live along the Pascagoula River. In southeastern Pascagoula, minorities are concentrated near the oil refinery. Generally, the African American neighborhoods in the study area lie outside of city limits (Figure 9).

Given that poor, minority communities are often relegated to underserved areas, their distribution has important implications for hazard vulnerability in coastal Mississippi. In coastal communities, waterfront property is more desirable, meaning the most marginalized communities live farther from the coast. While the northern tri-county area is removed from coastal flood hazards, tropical cyclone activity can still be devastating to the inland rural areas. During a hurricane, high winds threaten the structures of substandard, vulnerable housing and produce substantial debris. North of I-10, most zoning ordinances allow for mobile homes, and traditional homes tend to be older than in coastal areas, placing residents at risk.

The urban rural divide at I-10 also means vulnerable populations are removed from routine resources. Public transportation is sparse in even the most developed areas,

and nonexistent in the northern part of the coastal counties. This severely limits employment options and access to social services for individuals without a personal vehicle. In fact, there are no food pantries or free clinics north of I-10. In times of disaster, those vulnerable populations may have difficulty evacuating or be left with no supplies to shelter in place.

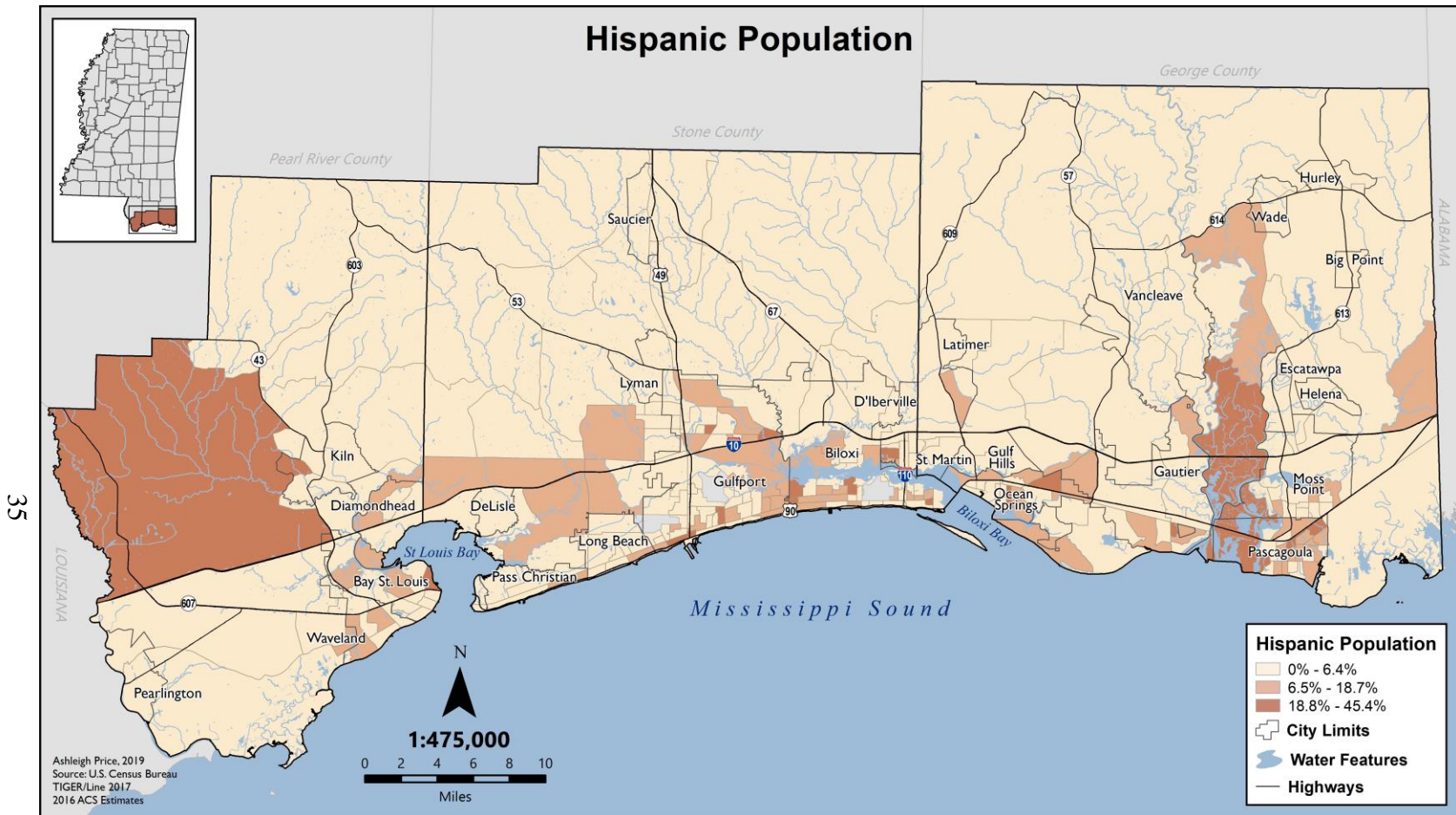


Figure 8. Hispanic Population

Hispanic population as percent of total block group population, Jenks classification (US Census Bureau, 2016 ACS 5-year estimates).

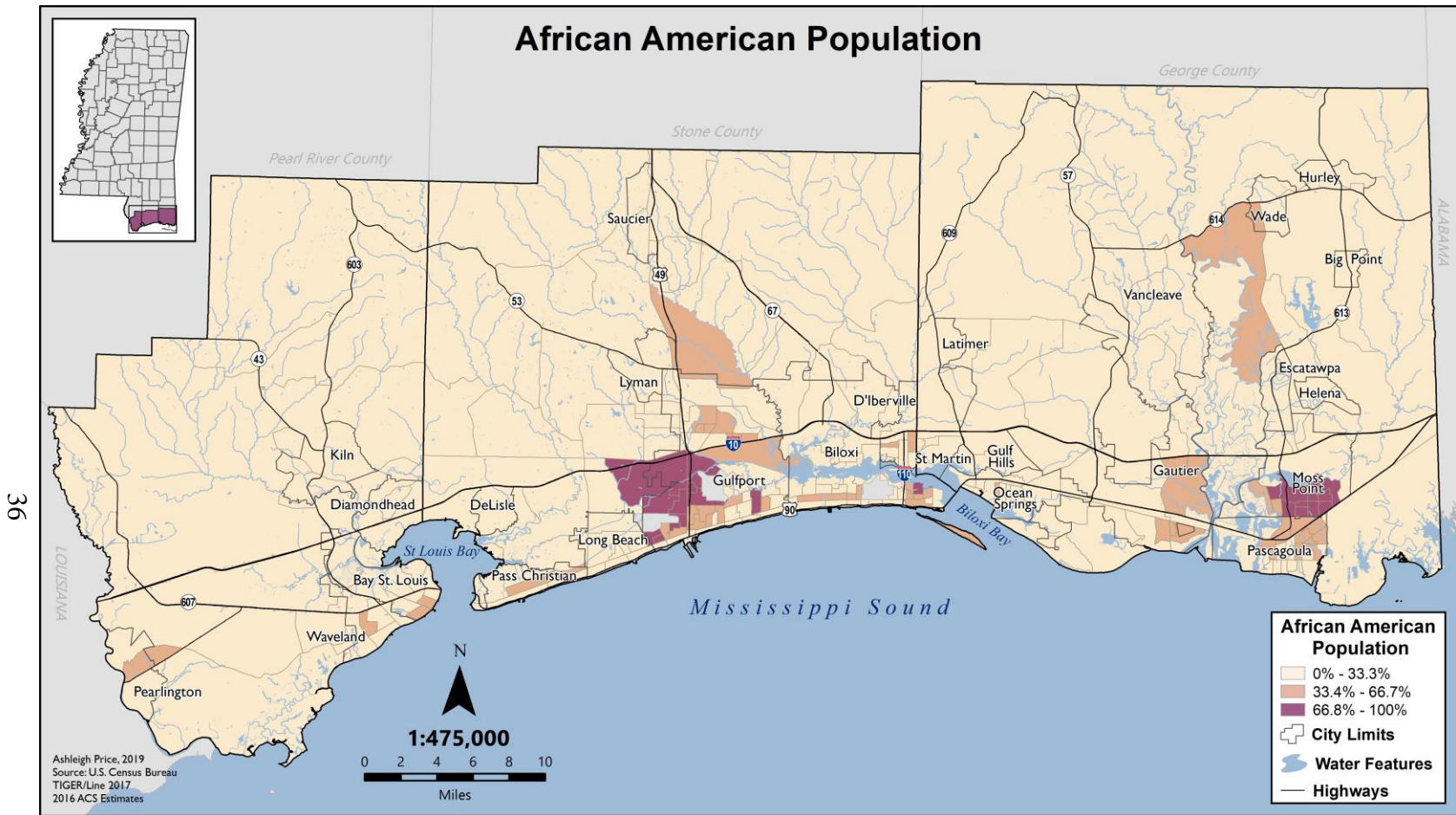


Figure 9. African American Population

African American population as percent of total block group population, equal interval classification (US Census Bureau, 2016 ACS 5-year estimates).

CHAPTER IV – METHODS AND ANALYSIS

Data Collection

Given the sensitive nature of offender identities, individual residence data was not available for this study. This research modeled offender residential patterns using a statistical proxy with the best available data. The goal was to select variables from the literature indicative of social disorganization and its constituent concepts: concentrated disadvantage, residential instability, and ethnic heterogeneity. The chosen socioeconomic data were the 2016 US Census Bureau American Community Survey (ACS) block-group level estimates.

Zoning maps and ordinances determined residential areas. Local GIS offices provided zoning district shapefiles (Table 3). The Mississippi Automated Resource Information System (MARIS), the Federal Emergency Management Agency (FEMA), Mississippi Geospatial Clearinghouse (MGC), the United States Census Bureau 2017 TIGER/Line repository, and the US Fish and Wildlife Service (FWS) provided polygon shapefiles for undeveloped areas (Table 4).

For both the coastal and riverine flood models, Hazus requires a user input digital elevation model (DEM), local stillwater elevations (SWEL), and wave setup. FEMA recommends a 1/3 arc second resolution DEM to optimize processing time and save disk space, while holding results statistically similar to finer resolutions (Scawthorn, Blais, et al. 2006; ASFPM 2009; Longenecker 2012; Remo, Carlson, and Pinter 2012). The United States Geological Survey (USGS) National Elevation Dataset (NED) provided four 1/3 arc-second DEMs. The FEMA Flood Insurance Studies (FIS) list the 100-year SWEL and wave setup for the coastal flood model (FEMA 2009b, 2017a, 2017b).

Table 3

Zoning Datasets

Location	Source
Harrison County	Harrison County Open Data Portal, Harrison County Tax Assessor
Jackson County, Gautier	Jackson County Information Systems
Hancock County	Gulf Regional Planning Commission
Pass Christian, D'Iberville, Long Beach	Geographic Information Services Department; Harrison County Board of Supervisors
Biloxi	City of Biloxi Department of Engineering
Gulfport	City of Gulfport
Pascagoula	City of Pascagoula
Bay St Louis	Slaughter and Associates Urban Planning Consultants
Ocean Springs	City of Ocean Springs Building and Planning Department
Waveland	Waveland.ms.gov (Digitized)
Moss Point	Cityofmosspoint.org (Digitized)
Northern D'Iberville	Diberville.ms.us (Digitized)
Gautier	Gautier-ms.gov (Digitized)

Zoning datasets used to determine residential areas in the suitability analysis.

Table 4

Spatial Datasets

Dataset	Source	Year
Non-Residential Zoning	Table 3	Various
Floodways	MARIS/FEMA	2017
NHD Waterbodies	MARIS	2018
NHD Water Areas	MARIS	2018
Inland Water Bodies	TIGER	2017
NWI Wetlands	US FWS	2018
State Parks	MARIS	1997
Military Installations	TIGER	2017
National Forest	MARIS	2017
WMAs/NWRs	MARIS	1997
Hazus Non-Residential Blocks	Hazus	2010
Census Zero Population Blocks	MARIS	2010
Census Unit Shapefiles	TIGER	2017
Building Footprints	MS GIS	2009
DEMs	USGS	2018
Crime Index Scores	ESRI	2018
Aerial Imagery	MARIS	2017

Secondary spatial datasets for suitability analysis, Hazus-MH modeling, and crime mapping

This research used block-group level crime data from ESRI Demographics. The available dataset contained aggregated 2010-2017 FBI Uniform Crime Reports (UCR) incidents, compiled for each reporting jurisdiction, normalized for population, and reported as a relative index on a national scale. Each block group has an index score for personal, property, and total crime (AGS and ESRI 2018), shown in figures 10, 11, and 12. As expected, collective rates of personal and property crime are highly correlated ($r = 0.84$). For more detailed comparison with the social disorganization model, disaggregated block-group level crime data was available for seven UCR offenses types: murder, robbery, assault, sexual assault, burglary, larceny, and motor vehicle theft.

For the purpose of this research *offender support services* are businesses or organizations that routinely provide resources for individuals on probation or parole. These include social services such as transitional housing and shelters, medical services including drug treatment and mental health services, and community resources like libraries, food pantries, and employment agencies. This research produced a list of offender support services based on the Mississippi Reentry Guide (FMS 2015), the United States Probation and Pretrial Services webpages (MSSP 2018b), and a cursory internet search.

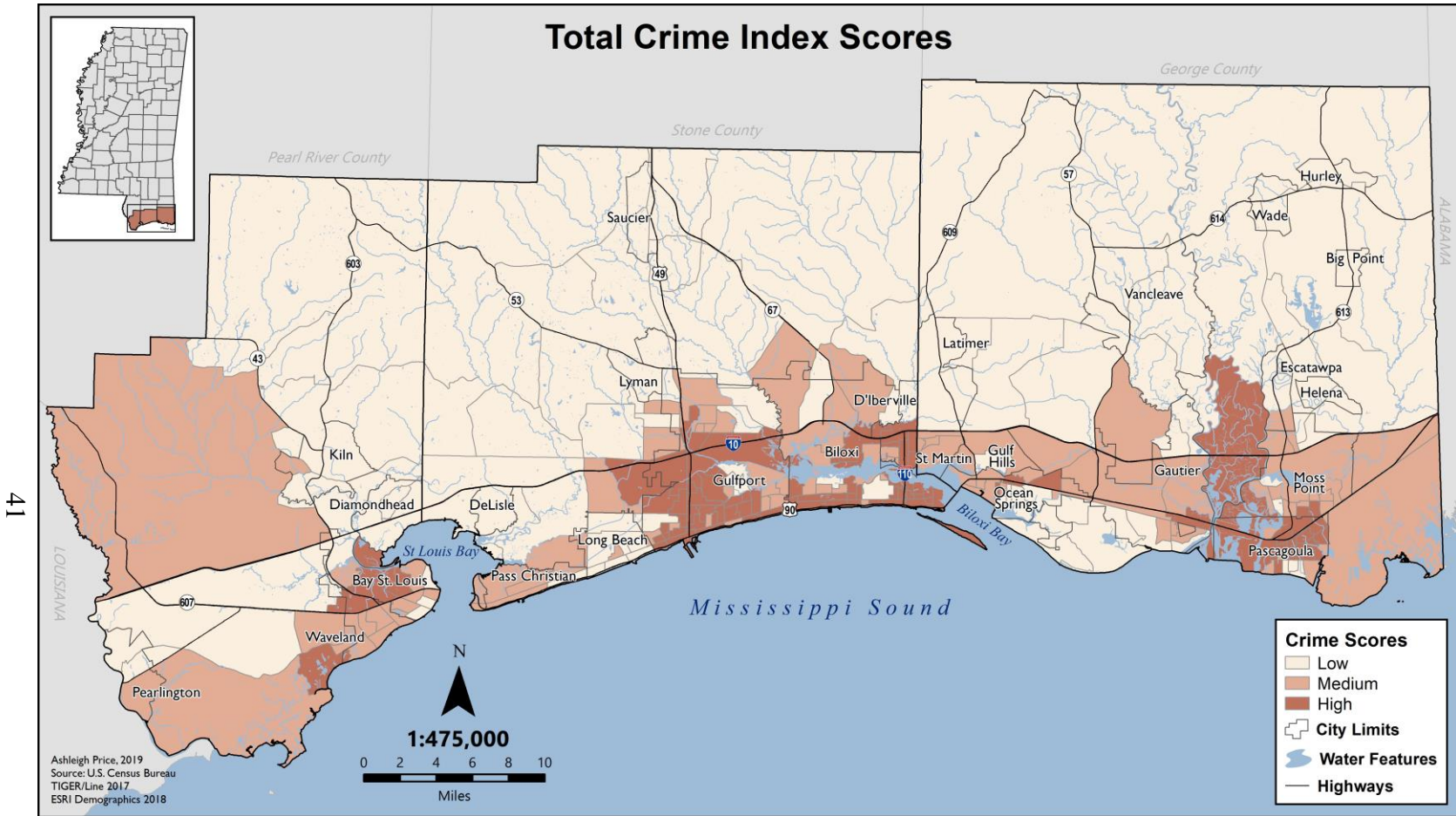
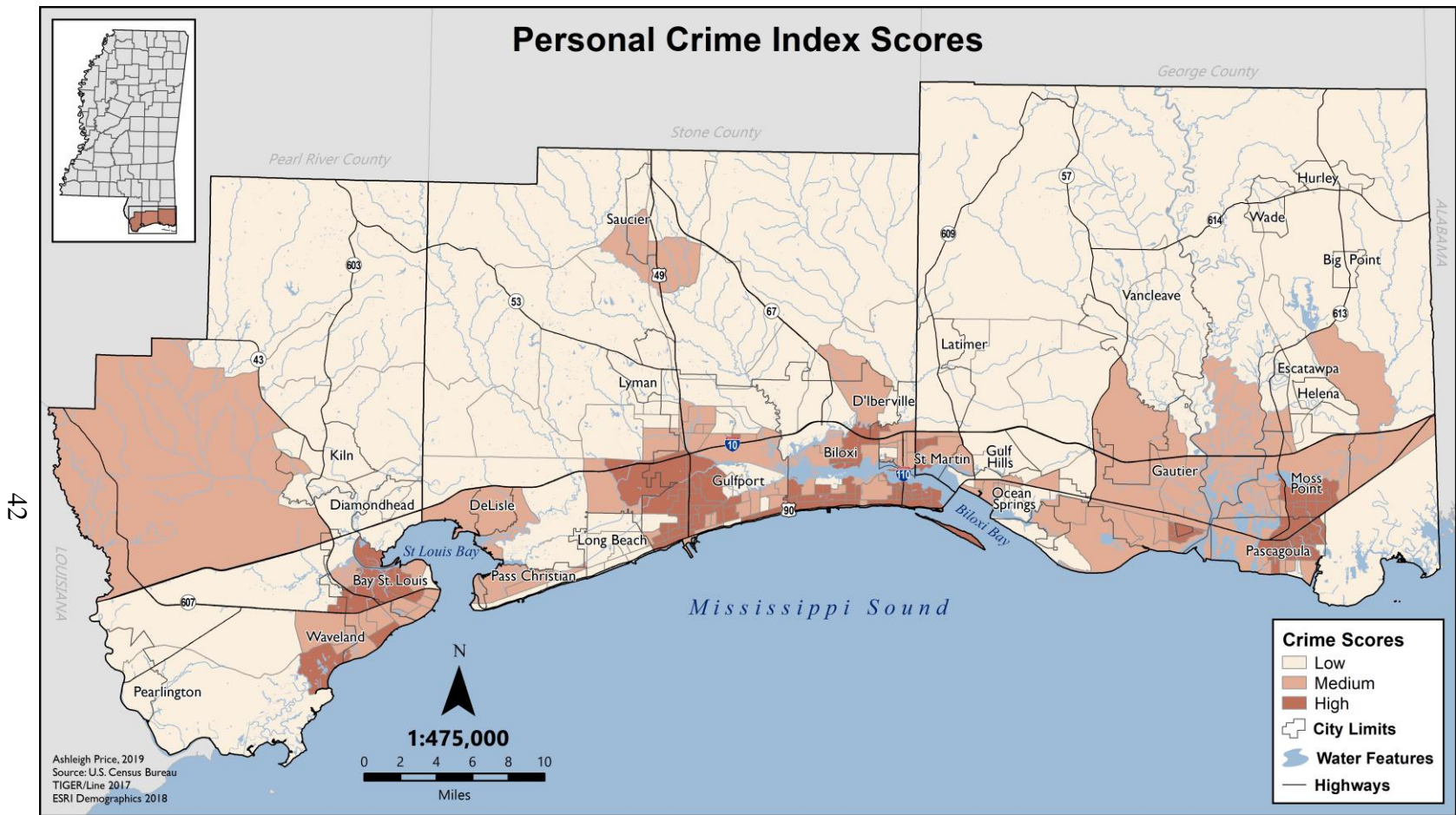


Figure 10. Total Crime Index Scores

Block-group total crime index scores, quantile classification (ESRI Demographics, 2018)



42

Figure 11. Personal Crime Index Scores

Block-group personal crime index scores, quantile classification (ESRI Demographics, 2018)

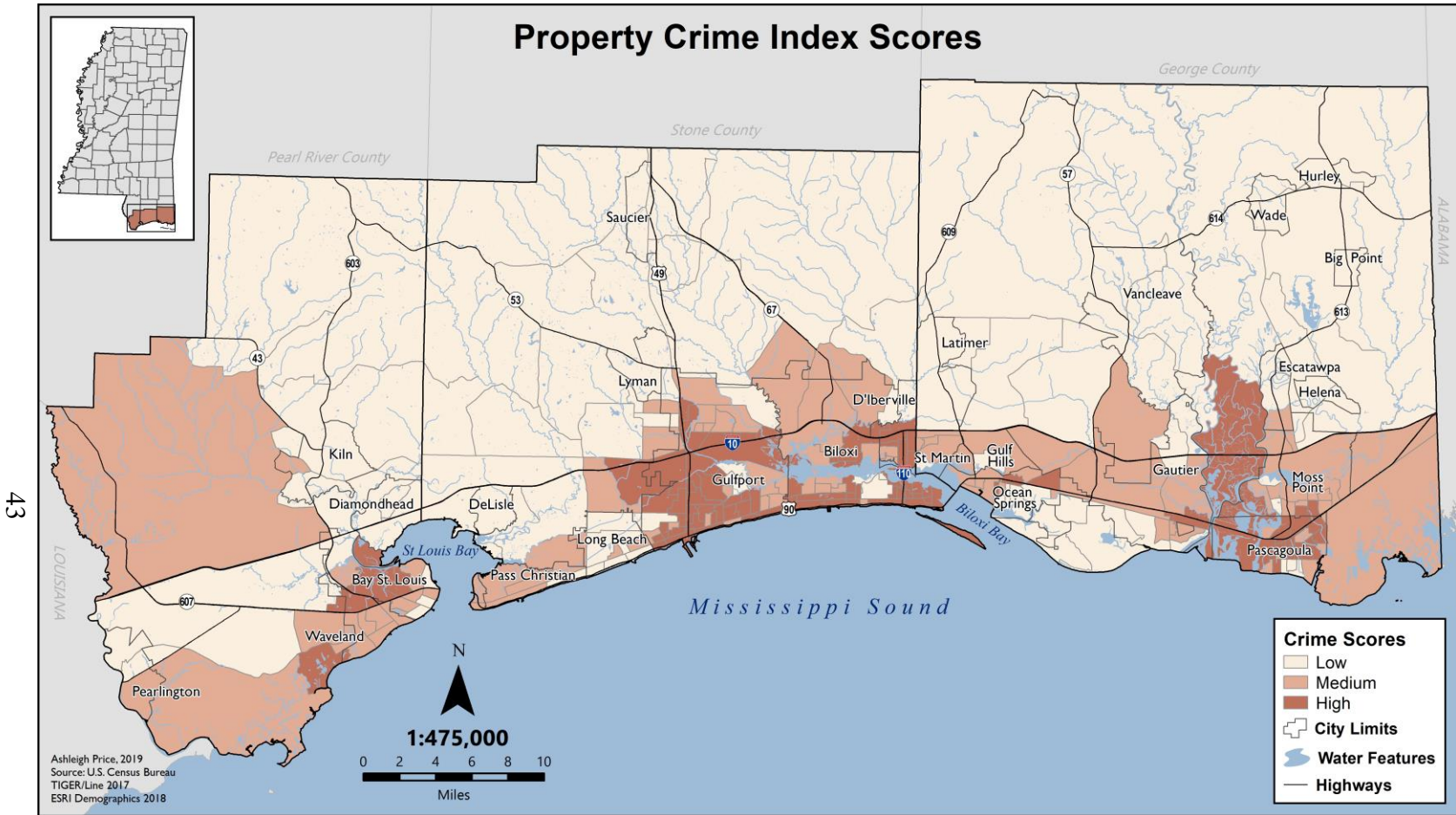


Figure 12. Property Crime Index Scores

Block-group property crime index scores quantile classification (ESRI Demographics, 2018)

Residential Suitability Analysis

The smallest scale available for the chosen socioeconomic data is the block group level, but numerous local features impact development and thus the actual spatial distribution of residential property within the block group. To match the scale of the Hazus results, it was first necessary to determine which census blocks contain residential areas and eliminate the non-residential blocks within the study area.

Local zoning ordinances determined non-residential areas. Most districts use traditional zoning designations (e.g. residential, commercial, or industrial), meaning zoning codes identified residential areas. SmartCode, Planned Unit Developments (PUDs), and Master Planned Communities (MPCs) contain mixed-use development. Residential areas in SmartCode districts contain all zones allowing for residential property (City of Pass Christian 2013; City of Gulfport 2015). Aerial imagery identified developed areas in PUDs and MPCs for digitization (Harrison County 2018; Jackson County 2018). Each jurisdiction was reclassified into residential and non-residential zoning and merged into a single shapefile, retaining the most recent data where overlap occurred. Figure 13 shows residential zoning in the study area and Appendix A shows the corresponding zone codes.

Much of the study area is zoned residential but does not contain residential development. Zoning in the northern swath of the counties is largely agricultural and includes land devoted to farming, forestry, or animal raising, as well as expansive areas of undeveloped and unpopulated land. The tri-county area contains many wildlife management areas (WMA), three national wildlife refuges (NWR), several military installations, and large forested areas under National Forest Service ownership. Inland

water bodies, wetlands, and dense stream networks, which are all common in coastal locales, are prevalent in the study area and several FEMA designated floodways prevent encroachment of the riverine floodplain. Additionally, a large portion of western Hancock County is designated as an acoustic buffer zone surrounding the John C. Stennis Space Center.

An ArcGIS model builder tool sequentially erased undeveloped areas. Beginning with the residential zoning shapefile, the erase tool removed polygon datasets for military installations, water features, national forests, WMAs, NWRs, state parks, and undeveloped wetlands from consideration. The explode function in ArcMap split disjunct polygons in the erase tool output. Select by location identified developed residential areas using the building footprints shapefile over the exploded output. Figure 14 shows the resulting suitable residential areas.

Select by location identified census blocks intersecting the suitable residential areas. The final step in the suitability analysis was to delete census blocks having zero residential property in the Hazus General Building Stock (GBS) inventory. Additionally, there is limited socioeconomic data for some block groups in the study area. This analysis did not consider the block groups surrounding Kessler Air Force Base (KAFB), the Naval Construction Battalion Center (NCBC), or the Gulfport-Biloxi International Airport (GPT). Figure 15 shows the resulting residential census blocks used in the analysis. The suitability analysis reduced the inland study area from 14,239 to 6780 census blocks, retaining 264 block groups.

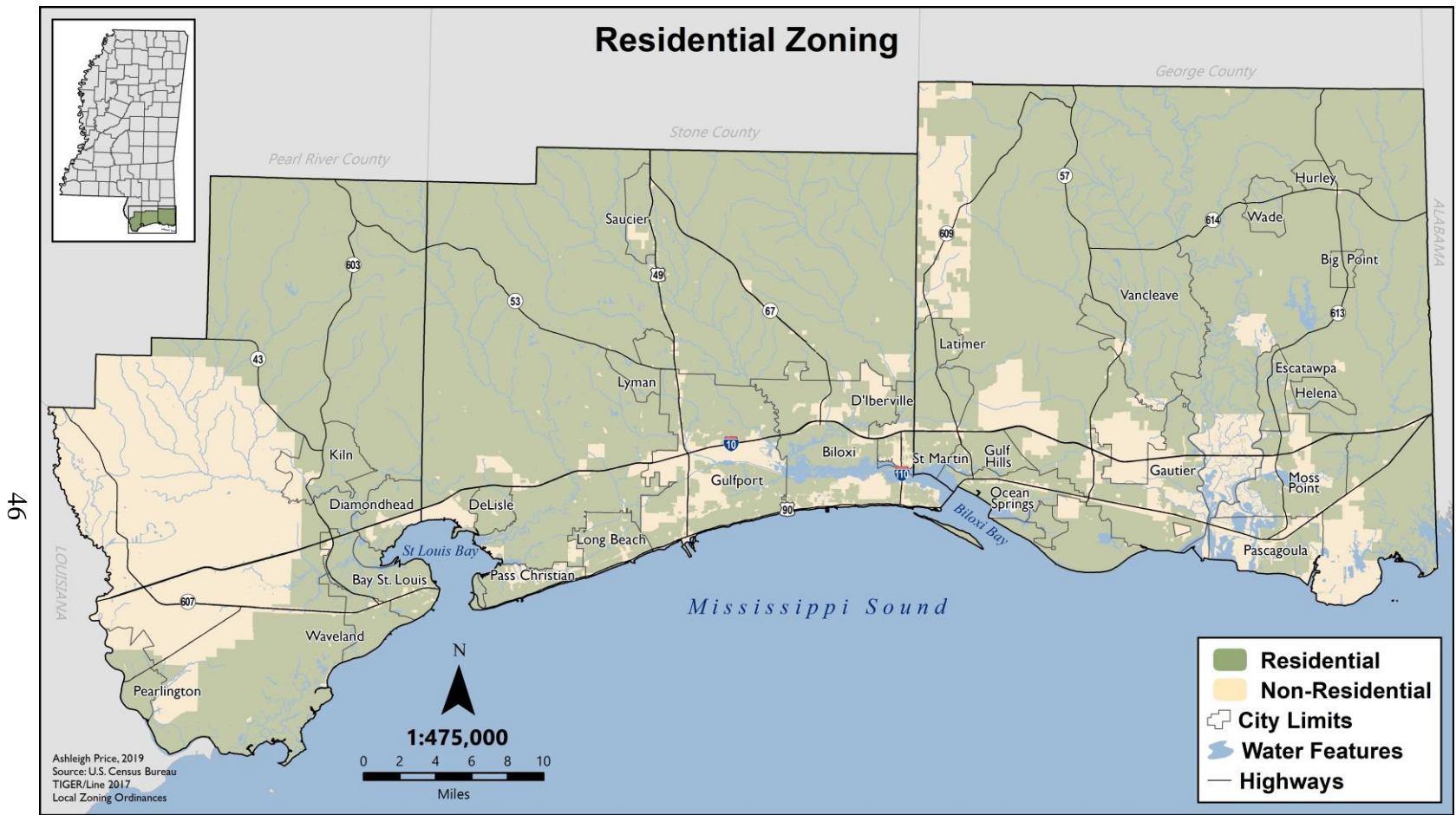


Figure 13. Spatial Distribution of Residential Zoning in the Study Area

Includes all zoning districts (residential, agricultural, and mixed-use) that allow for residential property.

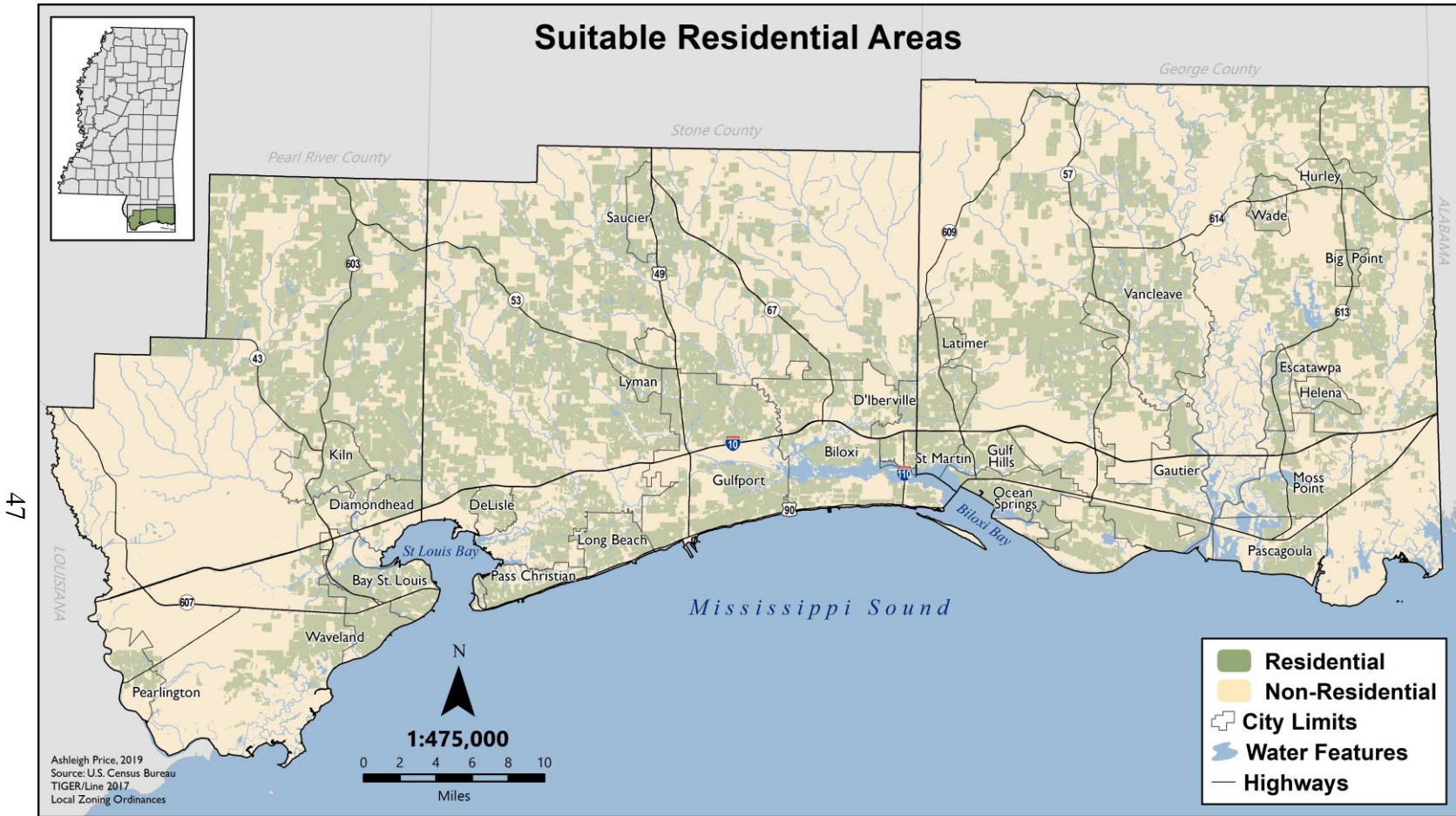


Figure 14. Suitable Residential Areas

Residential areas identified in the suitability analysis

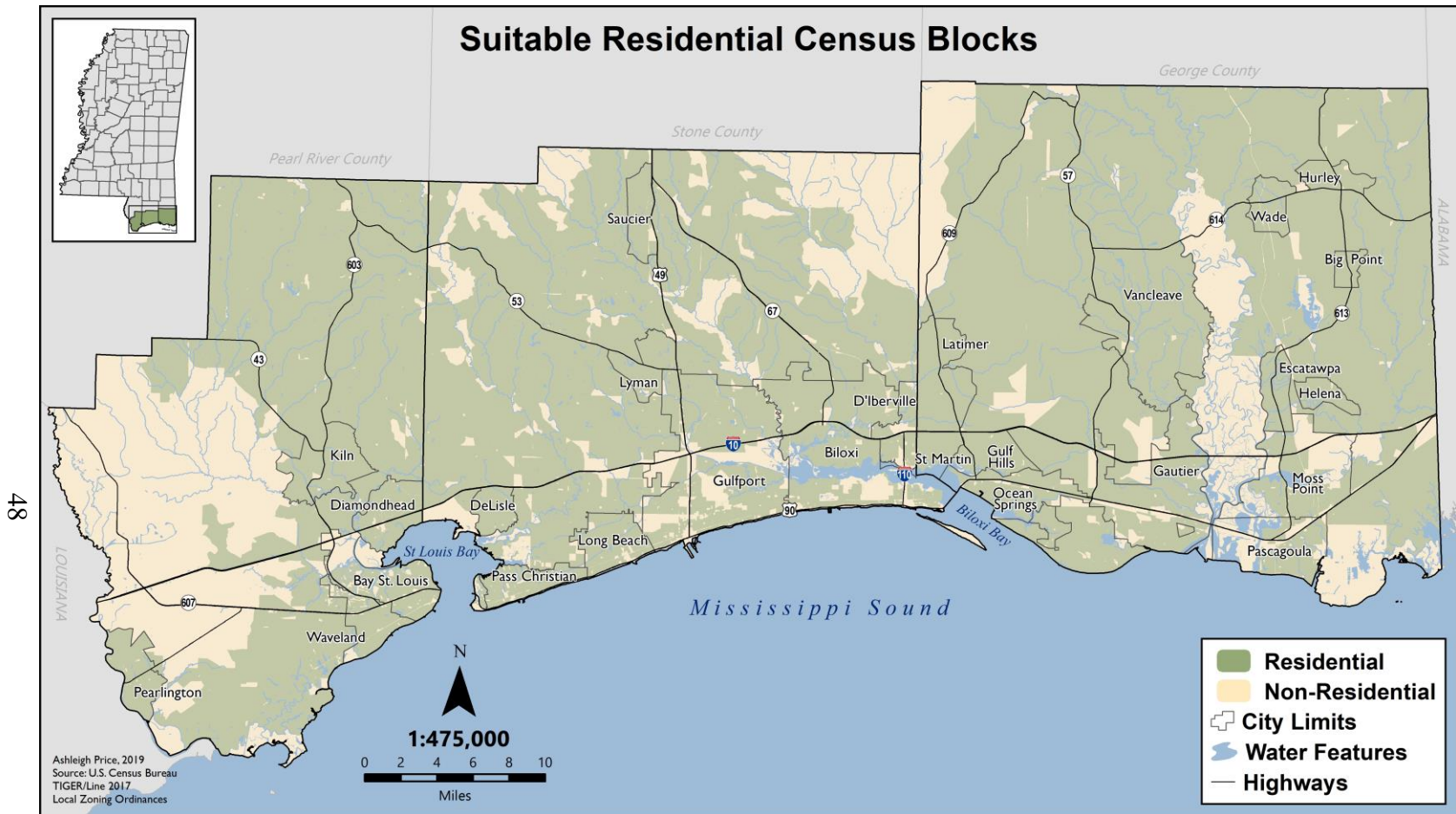


Figure 15. Suitable Residential Areas Aggregated by U.S. Census Block

Social Disorganization Model

Overview

This section describes the methodology for creating a statistical model of social disorganization using neighborhood characteristics. This research modeled *neighborhoods* at the block group level, the smallest unit available for the chosen socioeconomic data. A literature review produced 15 socioeconomic and demographic indicators (Table 5). Twelve of the variables are block-group level population proportions from 2016 US Census Bureau American Community Survey (ACS) estimates. Racial and ethnic heterogeneity and income inequality calculations followed methods outlined in the literature.

Pearson's correlation tested the indicators for bivariate relationships and figure 16 shows the correlation matrix. As expected, many of the socioeconomic indicators share a moderate to strong correlation ($r > 0.3$). A principal component analysis (PCA) consolidated the explanatory measures into a single Social Disorganization Index (SDI) for each suitable block group in the study area, where higher values indicate a more disorganized neighborhood.

Table 5

Social Disorganization Indicators

Variable	Rationale
Households in Poverty	(Krivo and Peterson 1996; Kubrin and Stewart 2006; Wehrman 2010; Harding, Morenoff, and Herbert 2013)
High School Diploma	(Parker and Mccall 1999; Ratcliffe and Mccord 2007; Wehrman 2010; Hipp and Kubrin 2016; Vogel and South 2016)
African American/Minority Population	(Sampson and Raudenbush 2004; Ratcliffe and Mccord 2007; Reynald et al. 2008)
Food Stamps/SNAP	(Tita, Cohen, and Engberg 2005; Demotto and Davies 2006; Wang and Arnold 2008; Stahler et al. 2013)
Single-Parent Households	(Baumer et al. 2003; van Wilsem 2009; Wehrman 2010)
Female-Headed Households	(Krivo and Peterson 1996; Tita, Cohen, and Engberg 2005; Ratcliffe and Mccord 2007; Groff and Lockwood 2014)
Employed in Service Occupation	(Pager 2003; Petersilia 2003; Pager, Western, and Sugie 2009; Mennis and Harris 2013)
Renter Occupied Households	(Morenoff, Sampson, and Raudenbush 2001; Wang and Arnold 2008)
Households Moved w/in Last 5 Years	(Morenoff, Sampson, and Raudenbush 2001; Bouffard and Muftic 2006; Miller, Caplan, and Ostermann 2016; Wickes, Britt, and Broidy 2017)
Racial/Ethnic Heterogeneity	(Hipp 2007; van Wilsem 2009; Prelog 2016; Wickes, Britt, and Broidy 2017)
Income Inequality	(Morenoff, Sampson, and Raudenbush 2001; Wang and Arnold 2008)
Population Density	(Morenoff, Sampson, and Raudenbush 2001)

Variable	Households in Poverty	Population 25 & Older w/out a HS Diploma	Households Receiving Food Stamps	Population Employed in Service Occupations	Female Headed Households	Single Parent Households	African American Population	Minority Population	Renter Occupied Households	Households Moved w/ in Last 5 Years	Race HI	Ethnic HI	Hispanic Population	Income Inequality	Population Density
Households in Poverty	1.0000														
Population 25 & Older w/out a HS Diploma	0.5532	1.0000													
Households Receiving Food Stamps	0.7710	0.5737	1.0000												
Population Employed in Service Occupations	0.4954	0.3684	0.5245	1.0000											
Female Headed Households	0.4360	0.3108	0.4707	0.2797	1.0000										
Single Parent Households	0.4623	0.3241	0.4545	0.2945	0.7347	1.0000									
African American Population	0.5193	0.3498	0.5507	0.3964	0.5534	0.4023	1.0000								
Minority Population	0.5358	0.3798	0.5540	0.4480	0.5355	0.4161	0.9551	1.0000							
Renter Occupied Households	0.4515	0.2144	0.4433	0.3730	0.2161	0.3232	0.3764	0.4412	1.0000						
Households Moved w/ in Last 5 Years	0.2876	0.1115	0.3236	0.2167	0.1753	0.2988	0.2041	0.2665	0.8251	1.0000					
Race HI	0.2427	0.1869	0.3006	0.3008	0.2998	0.3708	0.3810	0.5369	0.5346	0.5053	1.0000				
Ethnic HI	-0.0197	0.0690	0.0062	0.0149	0.0032	0.1368	-0.0237	0.1044	0.2235	0.2332	0.3803	1.0000			
Hispanic Population	-0.0010	0.0910	0.0404	0.0158	0.0142	0.1428	-0.0222	0.1055	0.2115	0.2282	0.3613	0.9837	1.0000		
Income Inequality	0.5717	0.3400	0.4871	0.4076	0.1691	0.1969	0.2739	0.2958	0.4356	0.2983	0.2195	-0.0542	-0.0296	1.0000	
Population Density	0.1665	0.0299	0.2223	0.2377	0.3036	0.2616	0.3340	0.3661	0.4113	0.3350	0.3946	0.1977	0.1957	0.0757	1.0000

Figure 16. Correlation Matrix

Pearson's correlation matrix for the chosen social disorganization indicators. Moderate to strong correlations ($r > 0.3$) are highlighted in yellow.

Socioeconomic Variables

Each variable was normalized over the block group. Poverty is the proportion of households with income below the poverty line in the last 12 months. The food stamp measure is the proportion of households receiving food stamps within the last 12 months. Educational attainment is the percentage of the population aged 25 and over without a high school diploma. The African American and Hispanic populations are the percentage of the total block group population. Female headed households is the proportion of female-headed households both with and without children. Single-parent households use the proportion of both male and female headed households with children under 18 and no spouse present. Renter occupancy rates are the proportion of rented households. The proportion of households having moved in last 5 years uses the proportion of total households, both renter and owner occupied, moving in 2010 or later. Service occupations uses the percent of employed individuals working in food service, healthcare support, personal care, and building maintenance, and excludes those in protective support occupations.

Racial/Ethnic Heterogeneity

To calculate racial heterogeneity, the block group populations were divided into four groups; White, African American, Asian, and Other (Hipp 2010; Bernasco and Block 2011). The Herfindahl Index (HI) uses the sum of the squared percentage of each race group (Hipp, Petersilia, and Turner 2010; Miller, Caplan, and Ostermann 2016). On the US Census form, race and ethnicity are not mutually exclusive. A second HI measures ethnic heterogeneity for the Hispanic and non-Hispanic population. In keeping with the literature, higher levels of homogeneity can indicate collective efficacy.

Subtracting the HI from 1 inverts the value so that it represents heterogeneity and can contribute positively to the social disorganization score. The maximum potential HI values are 0.75 for race and 0.50 for ethnicity (van Wilsem 2009; Hipp 2010; Prelog 2016). Figure 17 shows the HI formula adapted from Hipp (2010) where HI_{BG} is the Herfindahl index for each block group and G_j is the population proportion of each race or ethnicity (j) within that block group. Figures 19 and 20 show the spatial distribution of racial and ethnic heterogeneity in the study area.

$$HI_{BG} = 1 - \sum G_j^2$$

Figure 17. Herfindahl Index Formula

Income Inequality

Income inequality calculations followed the methods outlined in Wang and Arnold (2008). Localized Income Inequality (LII) uses the mean income for contiguous areas to assign a measure of relative wealth (Wang and Arnold 2008). This research used first order queen contiguity, meaning calculations were based on adjacent block groups sharing both common boundaries and vertices. Queen contiguity was chosen over rook contiguity (block groups sharing only linear boundaries) to increase the number of households used in the analysis.

The polygon neighbors tool determined queen contiguity for the study area. The results returned a table listing each block group and its neighboring block groups mean income, number of households, and weighted mean income. An Excel pivot table dissolved the results by block group to return the income values for the LII calculation. Figure 18 shows the block group LII formula.

$$LII_{BG} = \frac{\sum I_n / P_n}{I_{BG}}$$

Figure 18. Localized Income Inequality Formula

Localized Income Inequality (LII) formula taken from Wang and Arnold (2008).

The LII is simply the ratio of neighboring block groups mean income to the focus block group income. The numerator is the sum of weighted mean income for all contiguous block groups (I_n) divided by the total number of contiguous households (P_n), while the denominator (I_{BG}) is the focus block group mean income. LII values larger than 1 represent a lower mean income than adjacent areas. For example, an LII value of 2 represents a block group twice as poor as its neighbors. Figure 21 shows the spatial distribution of LII values in the study area.

Principal Components Analysis

Principal components analysis (PCA) consolidated the explanatory measures. First, a z-score conversion standardized the ACS, HI, and LII data. A Python script (Appendix B) converted the z-score data to a NumPy array, calculated the eigenvalues and eigenvectors of the covariance matrix, and returned the eigenvectors, factor loadings, and cumulative explained variance in the Python window.

All of the input measures contribute positively to social disorganization. Following the methods in Cutter, Burton, and Wood (2010), negative eigenvectors were multiplied by -1. This allows the eigenvectors, and thus the factor loadings, to have the correct directional influence on the total social disorganization score. Kaiser criterion (eigenvalues > 1) and varimax rotation in XLstat determined the principal components. Significant explanatory variables have factor loadings greater than 0.5 following the varimax rotation (Wood, Burton, and Cutter 2010).

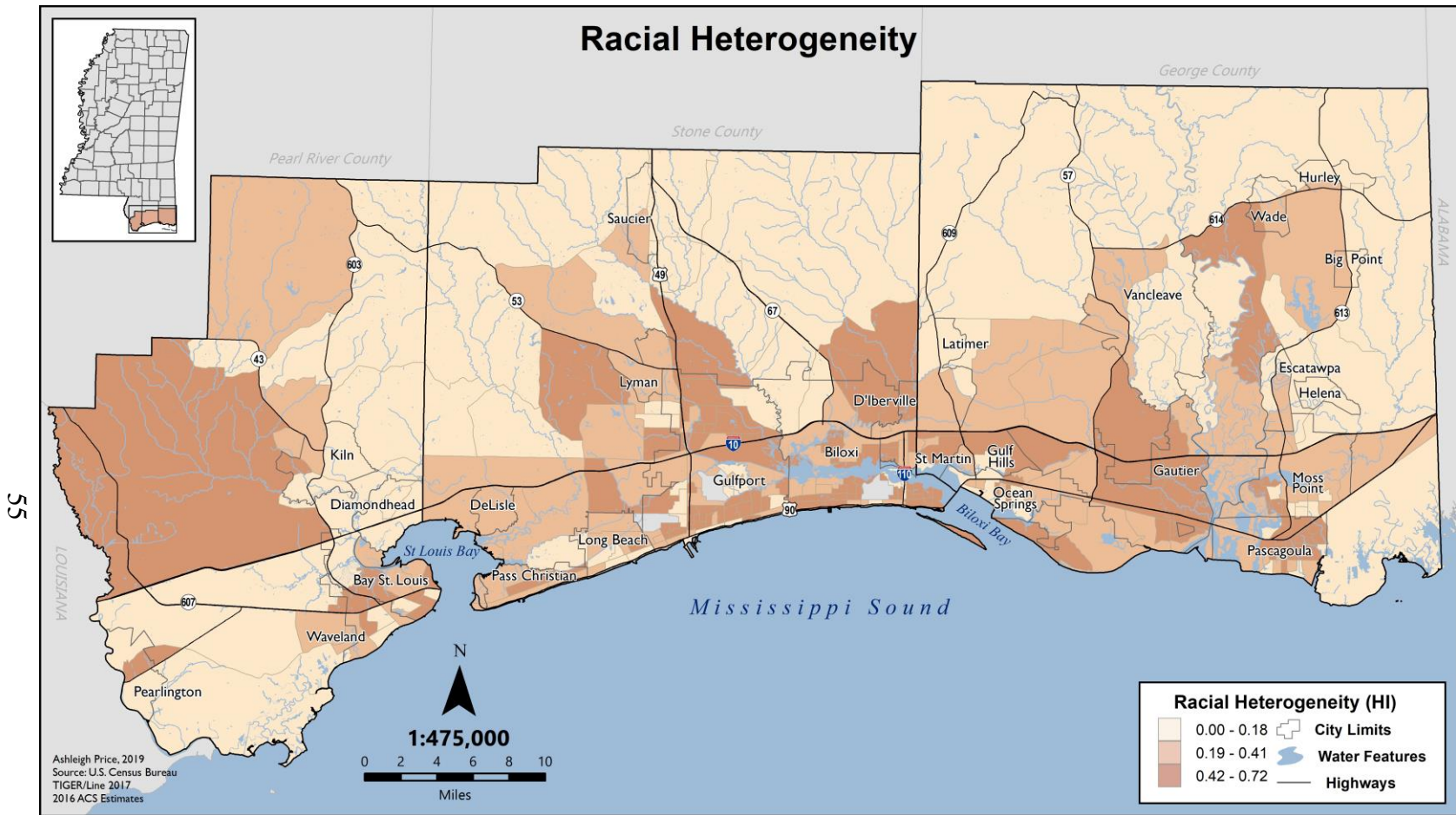


Figure 19. Racial Heterogeneity

Racial heterogeneity Herfindahl Index (HI). Jenks classification

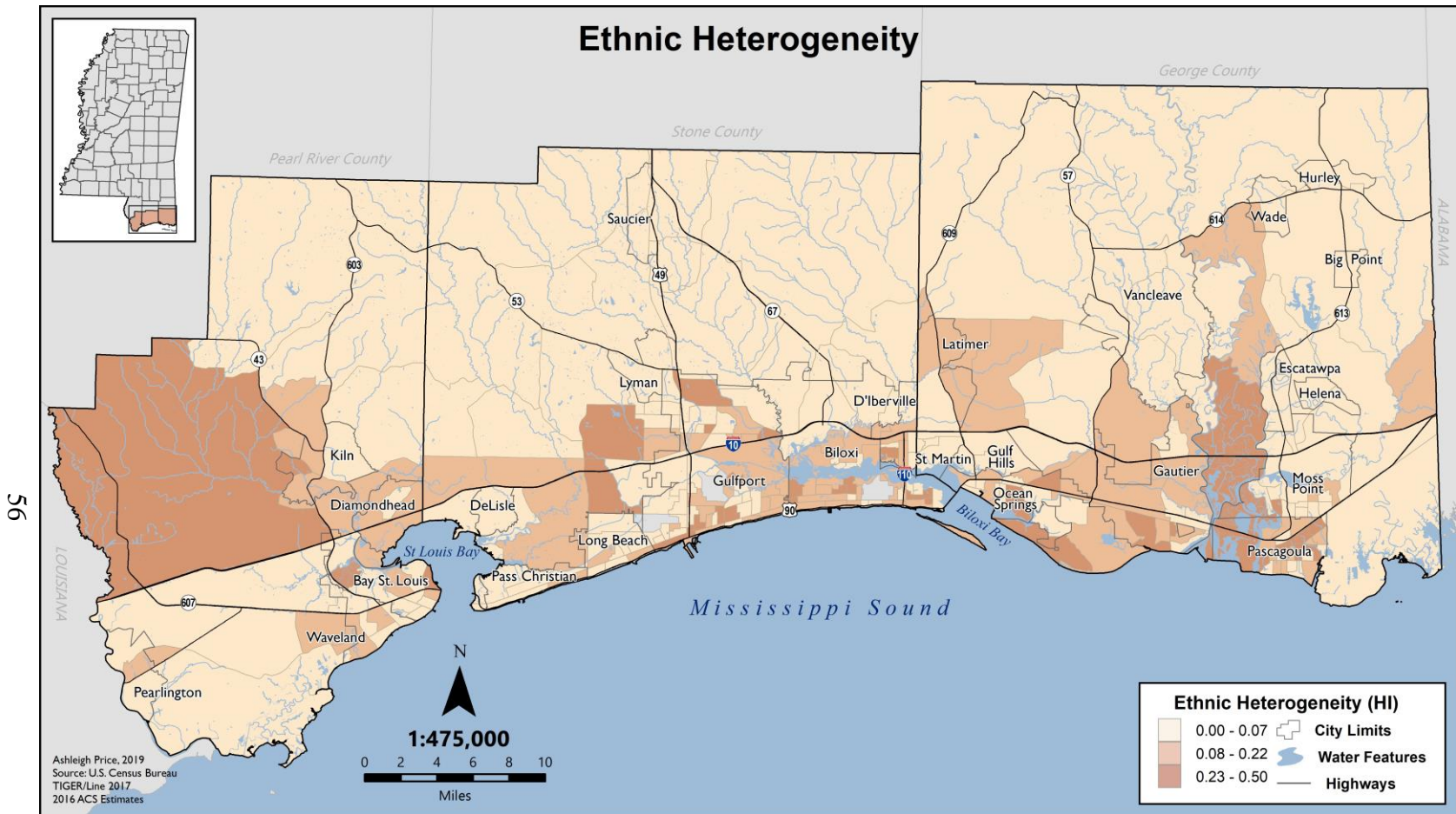


Figure 20. Ethnic Heterogeneity

Ethnic heterogeneity Herfindahl Index (HI), Jenks classification

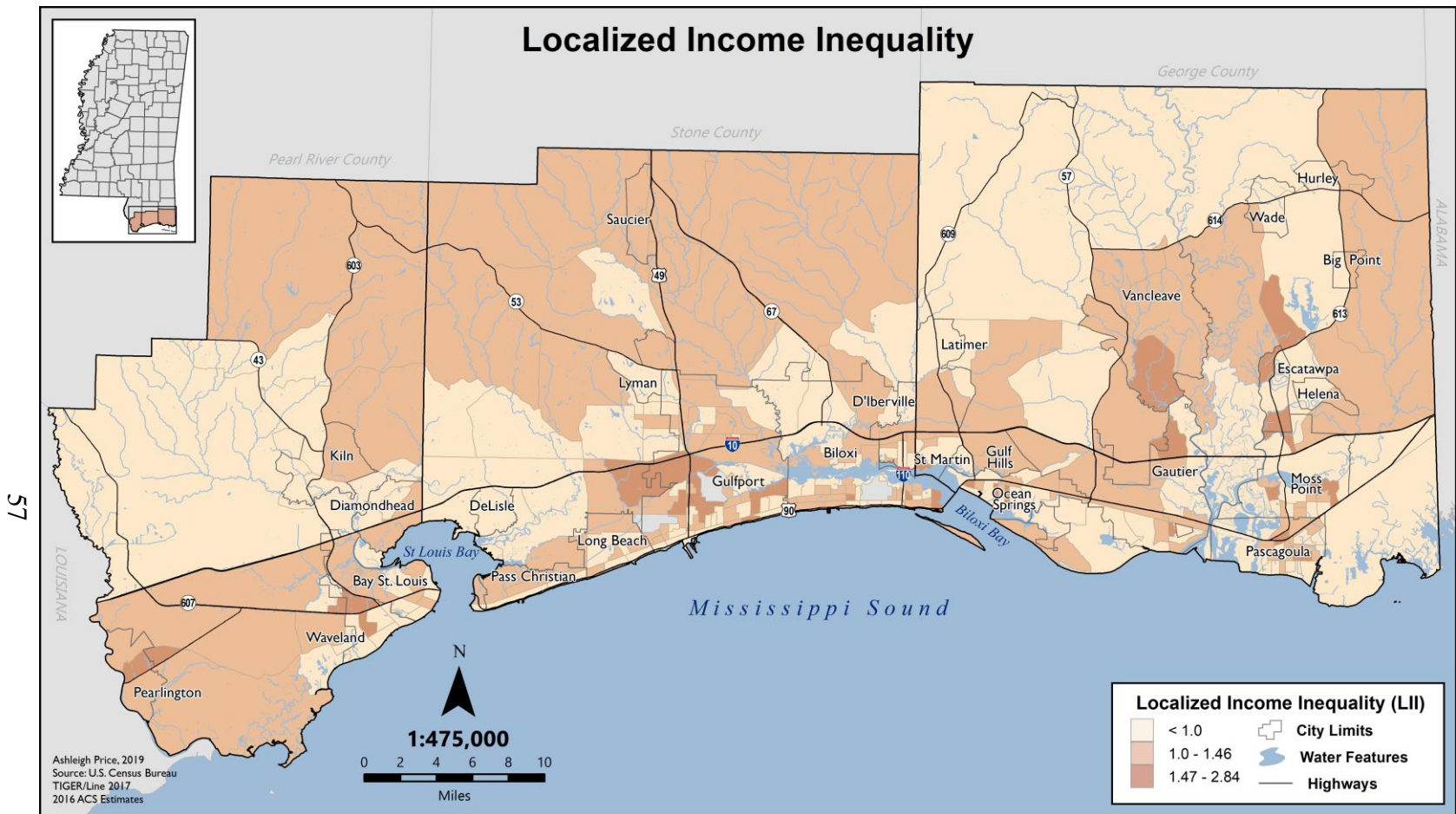


Figure 21. Localized Income Inequality

Block-group level Localized Income Inequality (LII) following methodology from Wang and Arnold (2008), Jenks classification

Components of Social Disorganization

The PCA reduced the original dataset to 4 components explaining 72.33% of the total variance (Table 6). The first component explains 38.39% of the variance and represents concentrated disadvantage. The largest factor loadings are for single parent and female-headed households and percent African American and minority population. Given the spatial isolation of African American neighborhoods in the study area, component one may also indicate the prevalence of unsupervised adolescents residing in underserved neighborhoods.

Both the percent Hispanic population and ethnic heterogeneity measures load highest on the second component, which explains 15.88% of the variance. There is a strong correlation ($r = 0.98$) between the Hispanic population and ethnic heterogeneity, isolating the two measures on the same component. The absence of an economic measure on the second component shows ethnic minorities in the study area tend to live in heterogeneous, but not necessarily disadvantaged, neighborhoods. Regarding social disorganization, ethnic heterogeneity represents possible cultural, social, and class distance and reduced collective efficacy.

Component three, residential instability, explains 9.42% of the variance. The highest factor loadings are for the proportion of renter occupied property, residents having moved within the last five years, racial heterogeneity, and population density. Regarding social disorganization, higher instances of residential mobility and racial heterogeneity can indicate reduced social ties and anonymity among residents. The inclusion of population density suggests urban neighborhoods are more associated with social disorganization.

Component four explains 8.65 % of the variance and represents economic inequality. There are five primary factor loadings; households in poverty, food stamp recipients, population without a high school diploma, percent of the workforce employed in service occupations, and income inequality. These indicators share moderate to strong correlations but have weaker relationships with the other explanatory measures. Statistically, this has the effect of isolating these measures on a single component. This is counterintuitive to the notion that poverty should contribute to concentrated disadvantage. The explanation lies in the spatial distribution of race and income in the study area. Minority populations are concentrated in block groups near the coast, but moderate to high poverty rates exist throughout the region. The inclusion of the income inequality measure on the fourth component suggests *relative* disadvantage exists in both the rural and urban portions of the study area.

Table 6

PCA Eigenvalues, Factor Loadings, and Explanatory Variables

Component (p)	Eigenvalue (λ_p)	Variance Explained	Primary Variables	Factor Loadings (R_{kp})
1. Concentrated Disadvantage	5.758	38.386%	Female-Headed Households	0.8264
			African American	0.7938
			Minority Population	0.7778
			Single Parent	0.6741
2. Ethnic Heterogeneity	2.382	15.880%	Hispanic Population	0.9784
			Ethnic Heterogeneity	0.9781
3. Residential Instability	1.412	9.416%	Renter Occupied	0.8653
			Moved in Last 5 Years	0.8629
			Racial Heterogeneity	0.5626
			Population Density	0.5069
4. Economic Inequality	1.297	8.646%	Poverty	0.7820
			No HS Diploma	0.7493
			Food Stamps	0.7346
			Income Inequality	0.7000
			Service Occupations	0.5549

Principal components for the Social Disorganization Index (SDI) determined via Kaiser Criterion and varimax rotation.

The method outlined in Jensen (2005), transformed the original dataset into a single Social Disorganization Score for each block group. The transformation formula shown in figure 22 represents the projection of the original dataset onto each component's axes. The new block group social disorganization score (SD_{BG}) is simply the sum of the eigenvectors (a_{kp}) for each component multiplied by the original value for each indicator (BV). The inclusion of eigenvectors in SD_{BG} calculation serves to weight each variable by its contribution to each component. The sum of the SD_{BG} values is a linear aggregation of the original dataset and is a unitless, social disorganization score (Jensen 2005; Wood, Burton, and Cutter 2010). A max-min rescaling converted these scores to the Social Disorganization Index (SDI). SDI values range from 0 to 1, with larger values indicating higher levels of social disorganization.

$$SD_{BG} = \sum a_{kp} BV$$

Figure 22. Transformation Formula for Principal Components Analysis

Transformation formula to project the original dataset onto the principal components' axes. Adapted from Jensen (2005).

Hazus-MH

Hazus-MH Overview

Hazus-MH 4.2.1 (Hazus) is a hazard modeling software developed by FEMA for use in ArcGIS. The Hazus General Building Stock (GBS) inventory contains census block level infrastructure and land use data. The GBS inventory incorporates statistics from the US Census Bureau, the US Department of Commerce, the US Department of Energy, and Dun & Bradstreet. Among other information, the GBS contains estimates of building square footage, proportion of structure and land use types, and demographic data from the 2010 US Census (FEMA 2012a).

Hazus model results can provide loss estimates for several hazards including hurricane winds and coastal and inland flooding. Executing a model over a user defined study region returns results for infrastructure damage, debris generations, short-term shelter needs, and the number of displaced persons, among other parameters. US Army Corps of Engineers (USACE) damage functions calculate loss estimates in the GBS inventory. Hazus allows the user to perform increasingly detailed analysis to improve accuracy in the loss estimates. In a Level 2 or 3 analysis, the user can modify the GBS to reflect actual replacement costs or local tax values and the results are useful in expenditure justification such as cost-benefit assessment of mitigation measures (Shultz 2017). Level 1 analysis with the default damage functions uses floodwater depth, wind speed, and land cover to estimate the percent damage to various structure types within a census block. The results of a level 1 analysis results are useful for comparative purposes within a region (Scawthorn, Flores, et al. 2006; Remo, Carlson, and Pinter 2012).

Remo, Pinter, and Mahgoub (2016) performed a level 1 analysis to create a comparative Flood Vulnerability Index within the state of Illinois. The authors used infrastructure loss estimates to rank jurisdictions in terms of flood risk and created a social vulnerability index using principal components analysis. The total loss estimates and social vulnerability scores were highest around Chicago, where population and infrastructure density are greatest. Proportional flood vulnerability, however, was most extreme in rural areas. Thus, the socioeconomic impacts may be more severe and longer lasting in small communities (Remo, Pinter, and Mahgoub 2016). These results are especially relevant to coastal Mississippi, a region with a striking rural-urban divide and high socioeconomic diversity.

Hurricane

The probabilistic hurricane model uses a 100,000-year simulated hurricane database and returns loss estimates for seven return periods/probabilities. Hazus searches the simulated storms affecting the study area for the maximum damage event at each return period. The wind speeds from these events and land cover are used to model loss estimates at the census tract level. It is possible that larger return period events may produce slower maximum wind speeds than more frequent events, although this is primarily an issue for large study regions (FEMA 2012b).

This research executed a probabilistic hurricane model for Hancock, Harrison, and Jackson Counties. The models returned residential loss estimates as the percentage of square footage at or above each damage state in each census tract. Figure 23, from the Hazus technical manual, shows the qualitative descriptions for each damage state. Moderate damage indicates some roof and window failure and the associated water damage to living quarters (FEMA 2018). This research used the used percentage of residential square footage in each census block with “At Least Moderate” damage.

Damage State	Qualitative Damage Description	Roof Cover Failure	Window Door Failures	Roof Deck	Missile Impacts on Walls	Roof Structure Failure	Wall Structure Failure
0	No Damage or Very Minor Damage Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof over, with no or very limited water penetration.	≤2%	No	No	No	No	No
1	Minor Damage Maximum of one broken window, door or garage door. Moderate roof cover loss that can be covered to prevent additional water entering the building. Marks or dents on walls requiring painting or patching for repair.	>2% and ≤15%	One window, door, or garage door failure	No	<5 impacts	No	No
2	Moderate Damage Major roof cover damage, moderate window breakage. Minor roof sheathing failure. Some resulting damage to interior of building from water.	>15% and ≤50%	> one and ≤ the larger of 20% & 3	1 to 3 panels	Typically 5 to 10 impacts	No	No
3	Severe Damage Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water.	>50%	> the larger of 20% & 3 and ≤50%	>3 and ≤25%	Typically 10 to 20 impacts	No	No
4	Destruction Complete roof failure and/or, failure of wall frame. Loss of more than 50% of roof sheathing.	Typically >50%	>50%	>25%	Typically >20 impacts	Yes	Yes

Figure 23. Hazus-MH Damage States for Residential Property

Damages states descriptive table taken from the Hazus-MH Hurricane Model Technical Manual (FEMA 2012).

Riverine Flood

Hazus generates a synthetic network of stream reaches by calculating flow direction over the DEM. Flow accumulation assigns a stream drainage area to each riverine segment. The user selects a minimum drainage area for analysis, between 0.25 and 400 square miles. Selecting a smaller drainage area increases precision in the model at significant expense of processing time (FEMA 2012a). To reduce processing time and spurious precision in stream density, this research used the default drainage area of 10 sq. mi. (Muthukumar 2005; Qiu, Wu, and Chen 2010). Figure 24 shows the modeled stream reaches.

Coastal Flooding

The coastal flood model uses data from 100-year flood events as initial conditions and outputs models for several return periods. Hazus requires the user to segment the study area shoreline into areas of similar physical characteristics such as rocky bluff, sandy beach, or open wetland (FEMA 2012a). Figure 25 shows the user dialog box for a shoreline segment. Required parameters are the 100-year SWEL, wave setup, and significant wave height. The transect that is closest to the center of each county shoreline provided the 100-year SWEL values used in the models (ESRI 2018). The user can enter a significant wave height or use the default depth-limited value calculated in Hazus. The Harrison and Jackson County FIS list significant wave heights for each transect and do not include wave setup in the 100-year SWEL (FEMA 2009a, 2017a, 2017b). The Hancock County FIS does not report the significant wave height or wave setup.

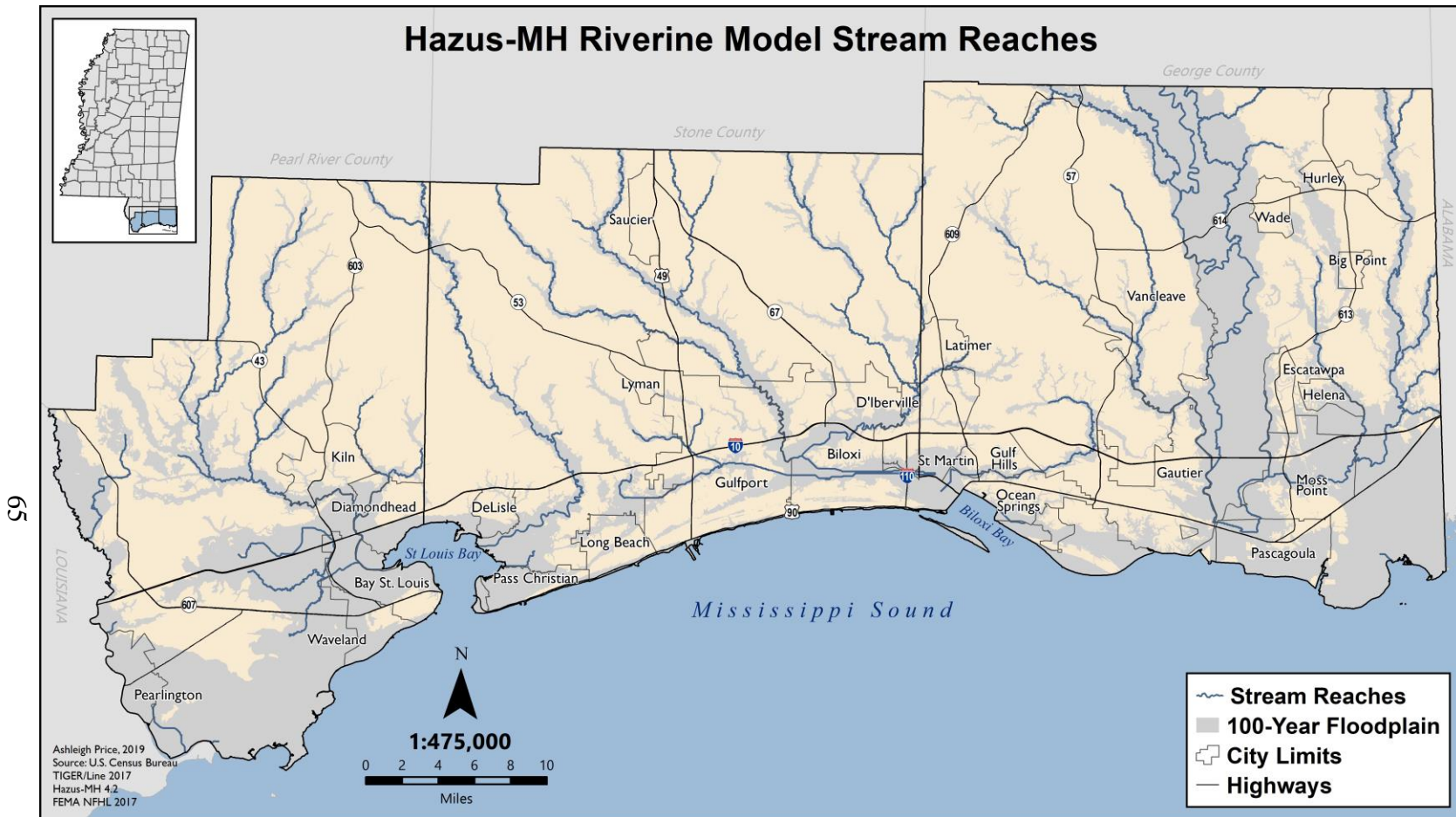


Figure 24. Hazus-MH Riverine Model Stream Reaches

Synthetic stream reaches used in the Hazus-MH riverine flood model.

Figure 25. Hazus Shoreline Characteristics User-Input

Example user-input dialog box for the Hazus coastal flood model.

Figure 26 shows the wave setup formula from the Hazus technical manual used to calculate the Hancock County parameters. $SWEL$ is the 100-year still-water elevation, W_s is the wave setup, and H_s is the depth limited significant wave height calculated in Hazus. The degree of shoreline exposure dictates the coefficient in the H_s formula, meaning increasing exposure increases the modeled wave height at the shoreline. The coastal flood model used the recommended maximum exposure parameter, “Exposed, Open Coast” (fetch > 50 miles) parameter and a reference elevation of 0ft NAVD 88 (FEMA 2012a).

$$H_s = 0.49(SWEL - W_s)$$

Figure 26. Wave Setup Formula

Wave setup for Hancock County was calculated using the significant wave height formula from the Hazus technical manual.

Table 7 shows the descriptive statistics for the 1% annual chance (100-Year) SWELs and the chosen model parameters. Given the small variation in SWELs within each county, the coastal flood models used a single shoreline segment for each county.

Table 7

Descriptive Statistics for 100-Year SWELs

Statistic	Hancock	Harrison	Jackson
Total Transects	38	68	55
Maximum	18.5ft	18.7ft	17ft
Minimum	17.1ft	16.2ft	11.1ft
Mean	17.8ft	17.8ft	14.7ft
Standard Deviation	0.46ft	0.59ft	1.16ft
Model SWEL	17.8ft	18.2ft	11.1ft
Significant Wave Height	8.7ft	7.7ft	4.5ft

Descriptive statistics for the 100-year SWEL values taken from FEMA FIS. All elevations are in feet NAVD 88.

The coastal and riverine flood models return the Flood Depth Grids (FDG) as a raster dataset. Integer values in the FDG are the modeled water depth above the reference elevation (0ft NAVD88) for each cell. Figure 27 shows the spatial extent of the FDG. Hazus uses the FDG in the USACE damage functions to model residential damage. The flood models return results as the number of residential square footage per census block. Figures 28, 29, and 30 show the percent of residential square footage with “At Least Moderate” damage in each suitable census block.

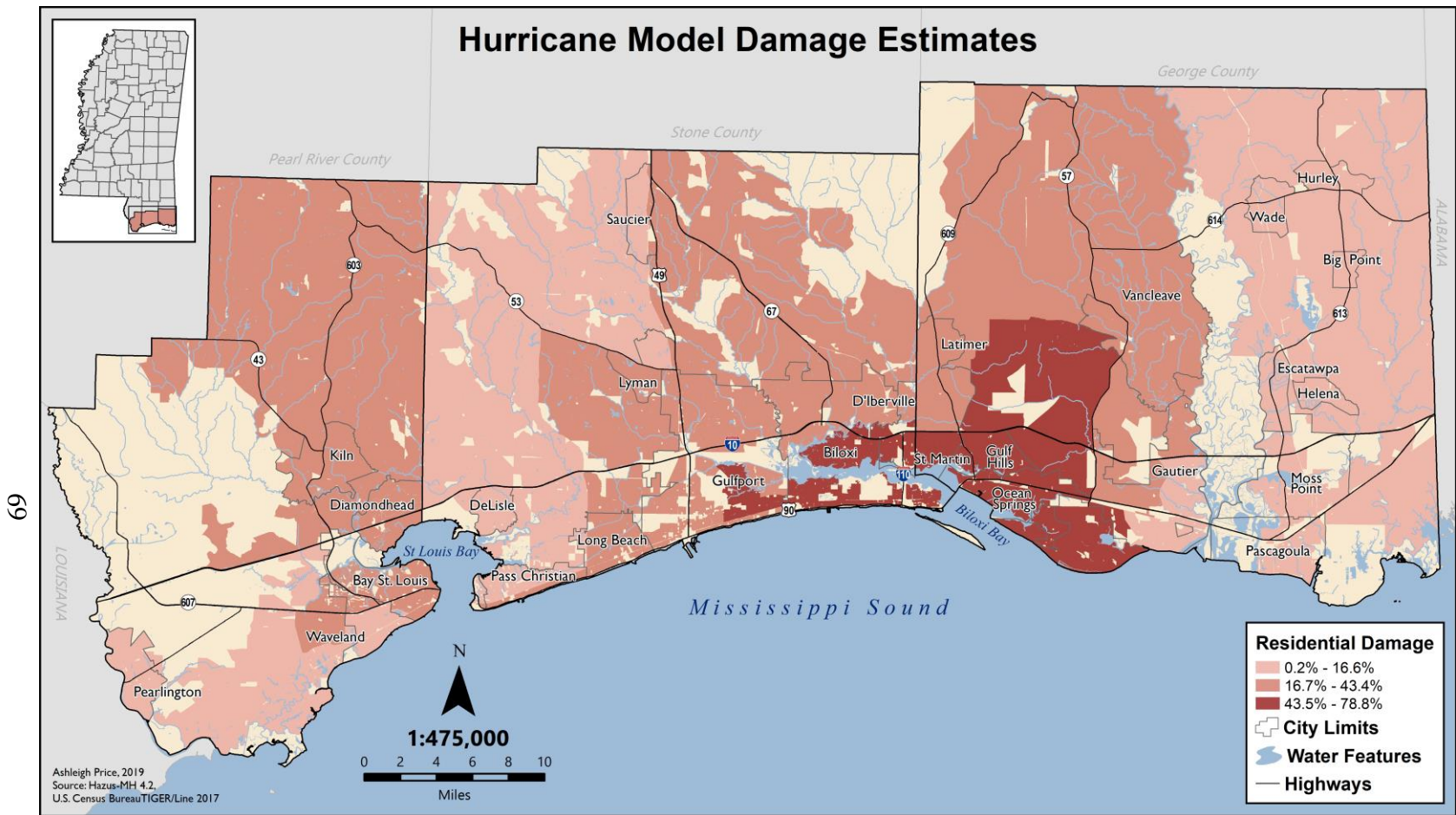


Figure 28. Hurricane Model Damage Estimates

Hazus-MH hurricane model residential damage estimates within suitable census blocks, Jenks Classification. Percentages are the proportion of residential square footages with “At Least Moderate” damage.

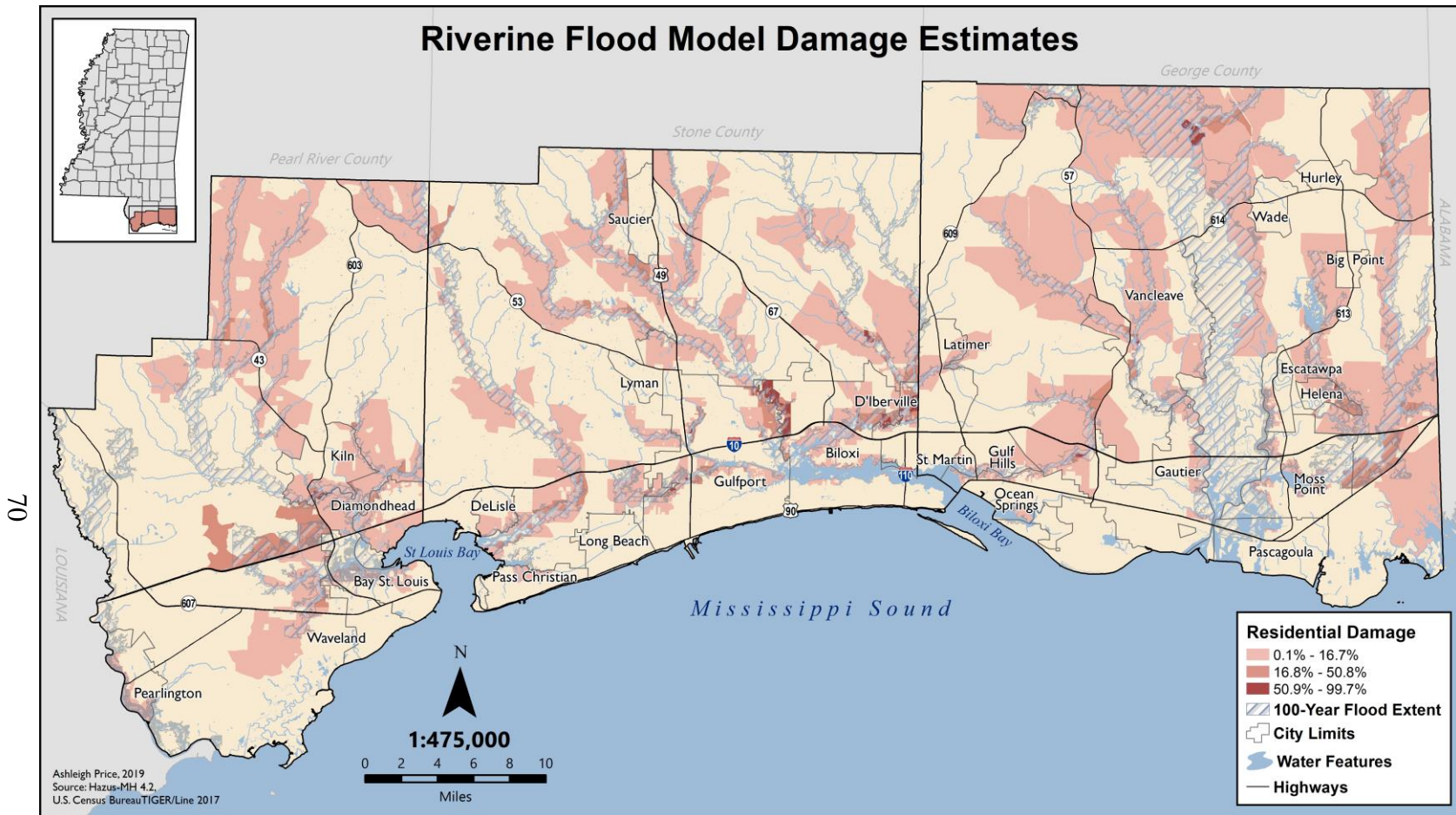


Figure 29. Riverine Flood Model Damage Estimates

Hazus-MH Riverine flood model residential damage estimates within suitable census blocks, Jenks Classification. Percentages are the proportion of residential square footages with "At Least Moderate" damage.

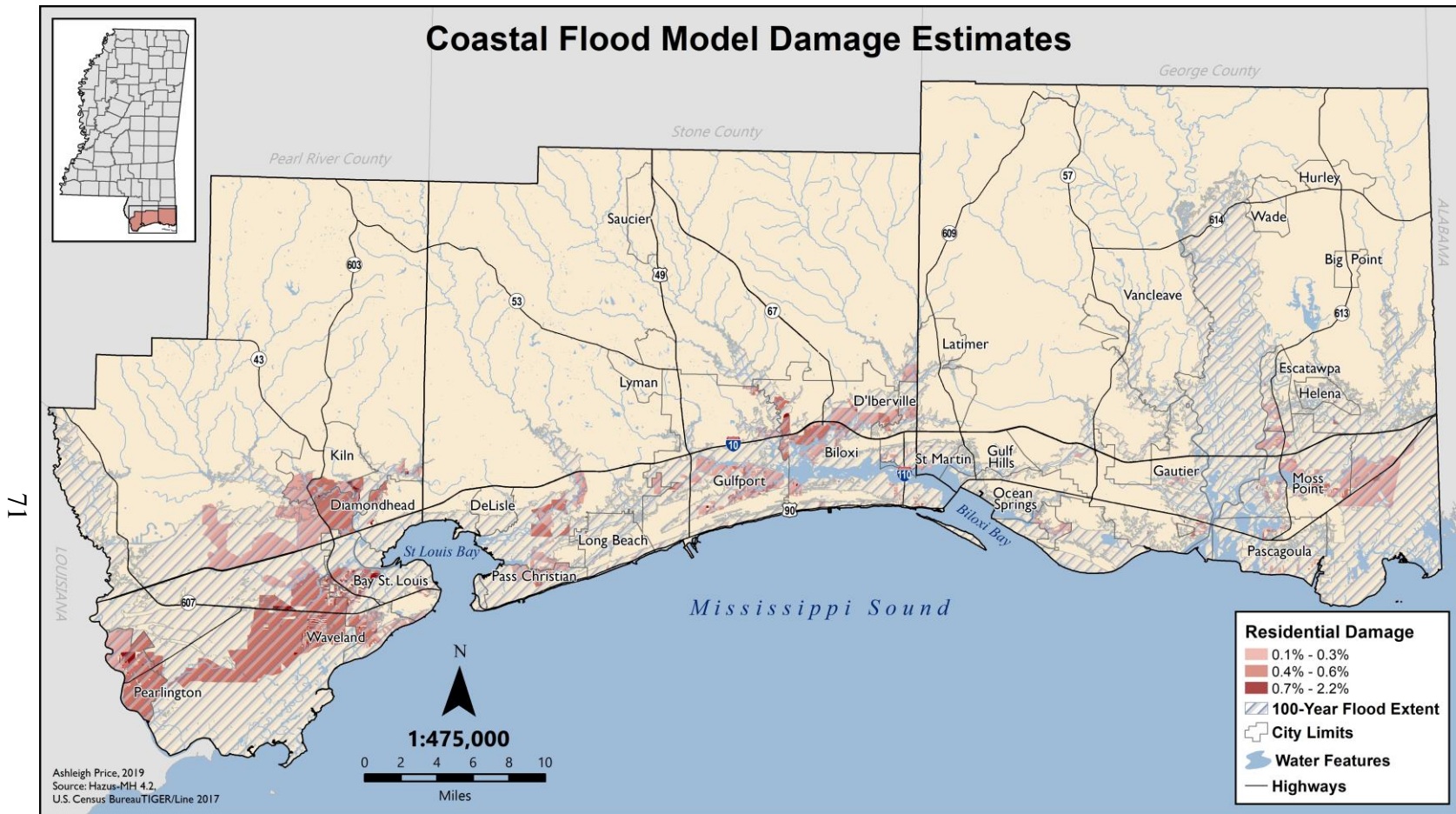


Figure 30. Coastal Flood Model Damage Estimates

Hazus-MH coastal flood model residential damage estimates within suitable census blocks, Jenks Classification. Percentages are the proportion of residential square footages with "At Least Moderate" damage.

Offender Support Services

A Python script (Appendix C) obtained business name and addresses from the Mississippi Reentry Guide (FMS 2015) and wrote those locations to a.csv file. The United States Probation and Pretrial Services office in Gulfport provides similar information for federal offenders as a pdf (MSSP 2018). An internet search cross-referenced the addresses to check for business closures, address formatting errors, and additional service locations. Geocoding the addresses with the ArcGIS World Geocoding Service in ArcMap resulted in a 98% match rate and returned 89 offender support services in the study area. A second python script (Appendix D) projected the point shapefile and reclassified the offender support services into nine categories based on the type of service provided: Probation and Parole Offices, Food and Clothing, Criminal Justice, Education and Life Skills, Employment, Health, Public Libraries, Shelter, and Substance Abuse Treatment.

The conditions of probation and parole require offenders to visit their community supervision officer on a regular basis. In areas like coastal Mississippi with sparse public transportation, travel presents an issue for offenders without access to a personal vehicle. In examining the availability of offender support services, this research measured the distance from disorganized neighborhoods to local community supervision offices. The feature to point tool in ArcMap identified block group centroids within each county. The near tool found the closest community supervision office and calculated the Euclidean distance. This research used Manhattan distance to approximate travel route distance from each disorganized neighborhood.

Methodology Summary

The goals of this research were to model offender residential patterns and physically vulnerable areas and to test the spatial relationship to offender support services and neighborhood crime rates. This chapter first described a vector data-based suitability analysis to identify residential census blocks. This chapter next presented the methodology for creating a statistical proxy of social disorganization using neighborhood characteristics. The third section detailed using hurricane and flood models in Hazus-MH to estimate the proportion of residential damage for the 100-year returned period. The final section described geocoding offender support services in the study area. The next chapter details the results of these analyses.

CHAPTER V – RESULTS

Overview

This chapter first discusses the results of the social disorganization model as a proxy for offender residential patterns and describes the spatial distribution and socioeconomic characteristics of disorganized neighborhoods. The second section details the Hazus-MH results and discusses the spatial distribution of modeled residential damage in the study area. The third section describes the location and availability of offender support services in each of the three counties. Finally, the chapter describes the spatial relationships between disorganized neighborhoods, physical vulnerability, and local crime rates.

Social Disorganization Model

This research used natural breaks (Jenks) classification of the SDI to identify disorganized neighborhoods. Jenks creates class breaks at the largest differences between values, highlighting inherent clusters within the data. Figure 31 shows the spatial distribution of the SDI using Jenks classification. Most of the study area exhibits low or medium social disorganization. The low SDI class contains 135 block groups, the medium classification has 88 block groups, and the high SDI class contains 41 block groups. In relating neighborhood characteristics to the presence of offenders, the upper SDI class represents the most disorganized neighborhoods. Of these neighborhoods, 24 block groups are in Harrison County and 17 block groups are in Jackson County.

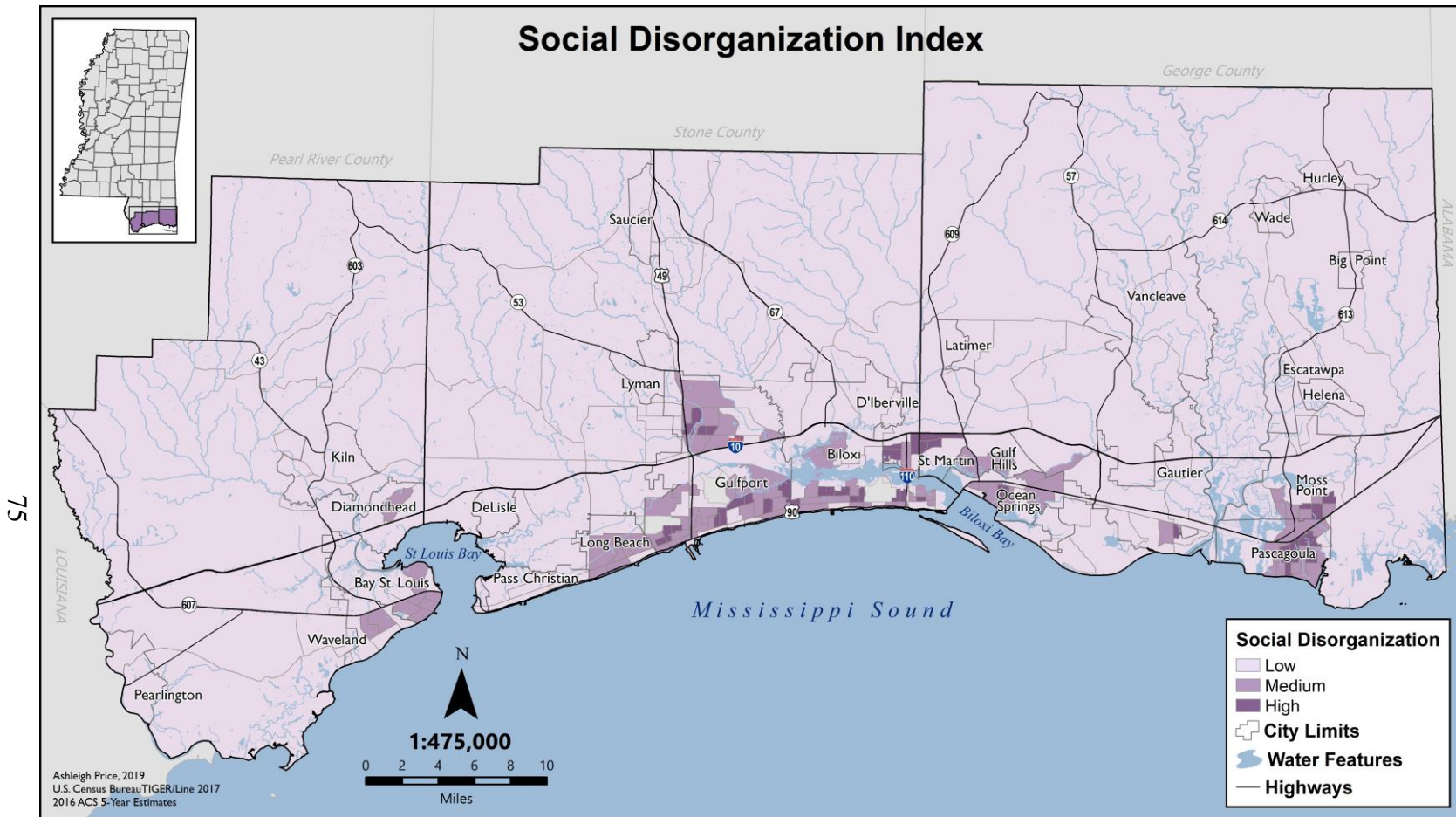


Figure 31. Social Disorganization Index

Social Disorganization Index (SDI), Jenks Classification.

In total, 54,408 people live in disorganized neighborhoods. Social disorganization is exclusive to the coastal section of the study area, although the proportion of the population living in disorganized neighborhoods varies considerably. Table 8 details the affected population within each of the coastal cities.

Table 8

Disorganized Neighborhood Populations

City	Disorganized Block Groups	Disorganized Neighborhood Population	Total City Population	Percent of Total City Population
Gulfport	13	17,056	71,265	23.93%
Biloxi	8	9,478	45,271	20.94%
D'Iberville	3	6,139	10,829	56.69%
St. Martin	3	5,630	8,245	68.28%
Ocean Springs	2	1,859	17,547	10.59%
Gautier	1	1,263	18,541	6.81%
Moss Point	3	3,766	13,652	27.59%
Pascagoula	8	9,217	22,163	41.59%
Total	41	54,408	207,513	26.22%

Affected populations for the upper SDI class using Jenks classification. (US Census Bureau, 2016 ACS 5-year estimates).

Gulfport

Figure 32 shows the spatial distribution of disorganized neighborhoods in Gulfport. Social disorganization in northern Gulfport is present four block groups north of Interstate 10 and east of Highway 49. The area is largely residential, and households are 38.6% renter occupied, with 37.6% having moved in 2010 or later. Female-headed households are 29.6% of the total, although the rate of single-parent households is much lower at 19.0%. The average poverty rate is 18.6%, 16.9% of residents do not have a high school diploma, and 16.3% of employed persons work in service occupations. There is little income inequality with surrounding block groups (LII = 1.05). Racial heterogeneity is high (HI = 0.48) as minorities are 45.8% of the total population.

In coastal Gulfport, social disorganization appears in block groups adjacent to the NCBC. This area has a high proportion of female-headed households (38.2%), and a large minority population (79.6%). High school completion rates are better than the state average, but 19.9% of employed people work in service occupations. Households are equally renter and owner-occupied, although 50.8% of residents have moved within the last five years. The poverty rate is 37.2% and 21.2% of households receive food stamps.

South of GPT, four block-groups show high social disorganization. There is no income inequality (LII= 0.98) although the poverty rate is 21.5% and 21.2% of households receive food stamps. High school completion rates are above the state average and 19.9% of employed people work in service occupations. The area is mostly single-family homes, although there are some mobile home communities and apartment complexes. Renter occupied households are 61.5% of the total with the same proportion having moved in 2010 or later.

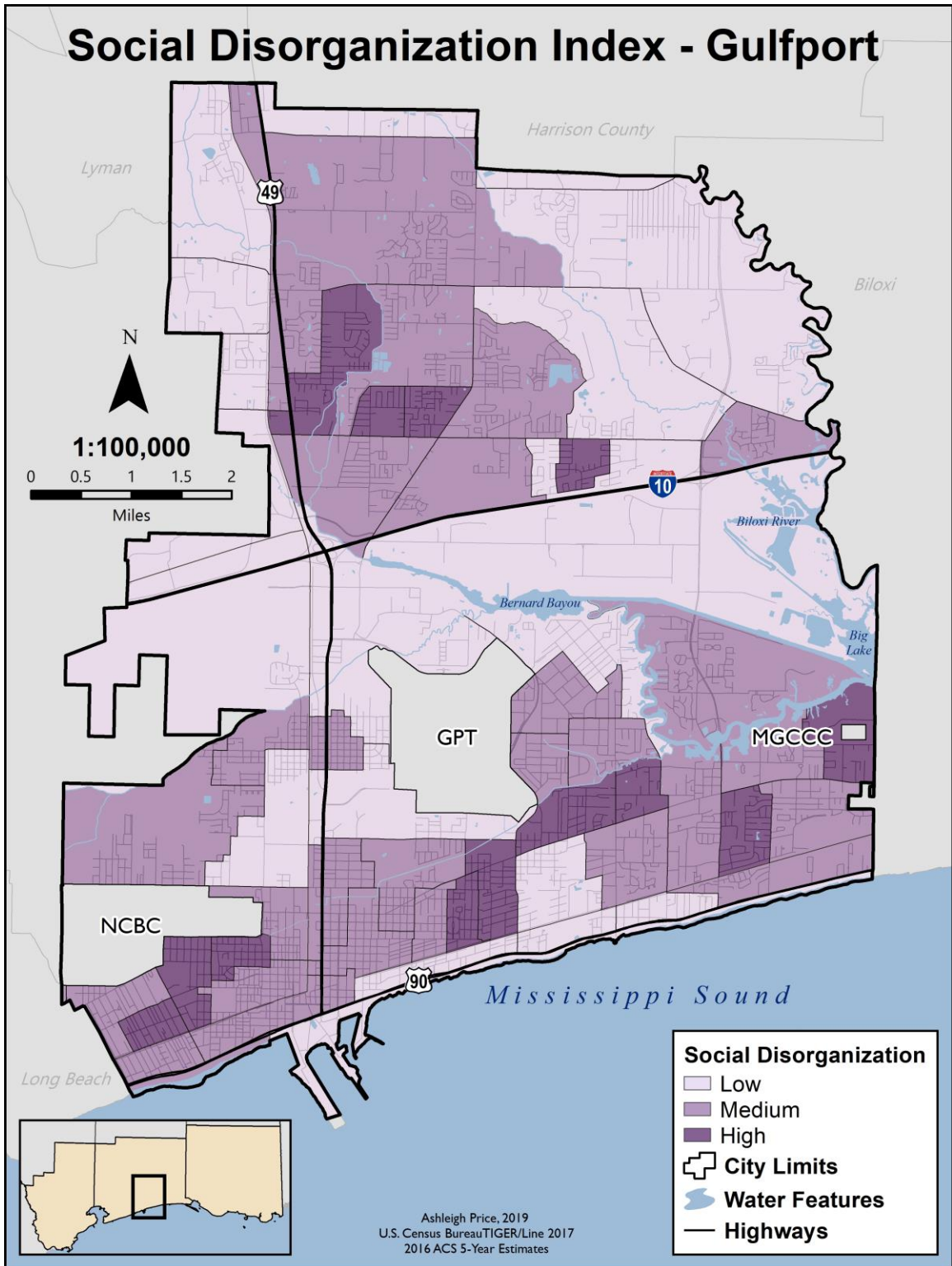


Figure 32. Gulfport Social Disorganization Index

In the block group south of Big Lake, income inequality is slightly higher than in the area around GPT (LII = 1.35). The poverty rate is 20.0%, 16.0% of residents do not have a high school diploma, and 10.1% of employed persons work in service occupations. Apartments near the Mississippi Gulf Coast Community College (MGCCC) Jefferson Davis Campus likely influence residential instability rates. In this area, 93.2% of households are renter occupied and 81.3% have moved within the last 5 years.

Biloxi

Figure 33 shows the spatial distribution of disorganized neighborhoods in Biloxi. The most disorganized neighborhood in Biloxi is also adjacent to the MGCCC campus. Most indicators are on par with the county average, although there is some income inequality with adjacent block groups (LII = 1.27). Residential instability is the largest contributor to social disorganization. There are numerous apartment complexes in this neighborhood and all the households are renter occupied with 88.7% of residents having moved within the last five years. This is likely due to the presence of students, rather than military residents as active duty service members are only 1.1% of the total block group population.

High SDI values are present in 6 block groups around KAFB. The block group south of Bayou Laporte has high residential instability as 83.2% of households are renter occupied and 71.0% moved in 2010 or later. This is in part due to the large proportion of military members residing in this neighborhood. The 224 active duty service members in this block group represent only 14.9% of the total population but make-up as many as 44.5% of the total households. The remaining five disorganized block groups near KAFB have no military residents, yet the majority (65.5%) of homes are renter-occupied and

53.9% of residents moved within the previous five years. Collectively, income inequality is moderate (LII = 1.22) but the average poverty rate is 34.9%, and 34.4% of households receive food stamps.

A single block group in eastern Biloxi has a high SDI value. The neighborhood has low residential instability as only one-third of homes are renter occupied or moved within the past five years. Instead, a large minority population (89.4%) and a prevalence of female-headed households (39.2%) contribute social disorganization.

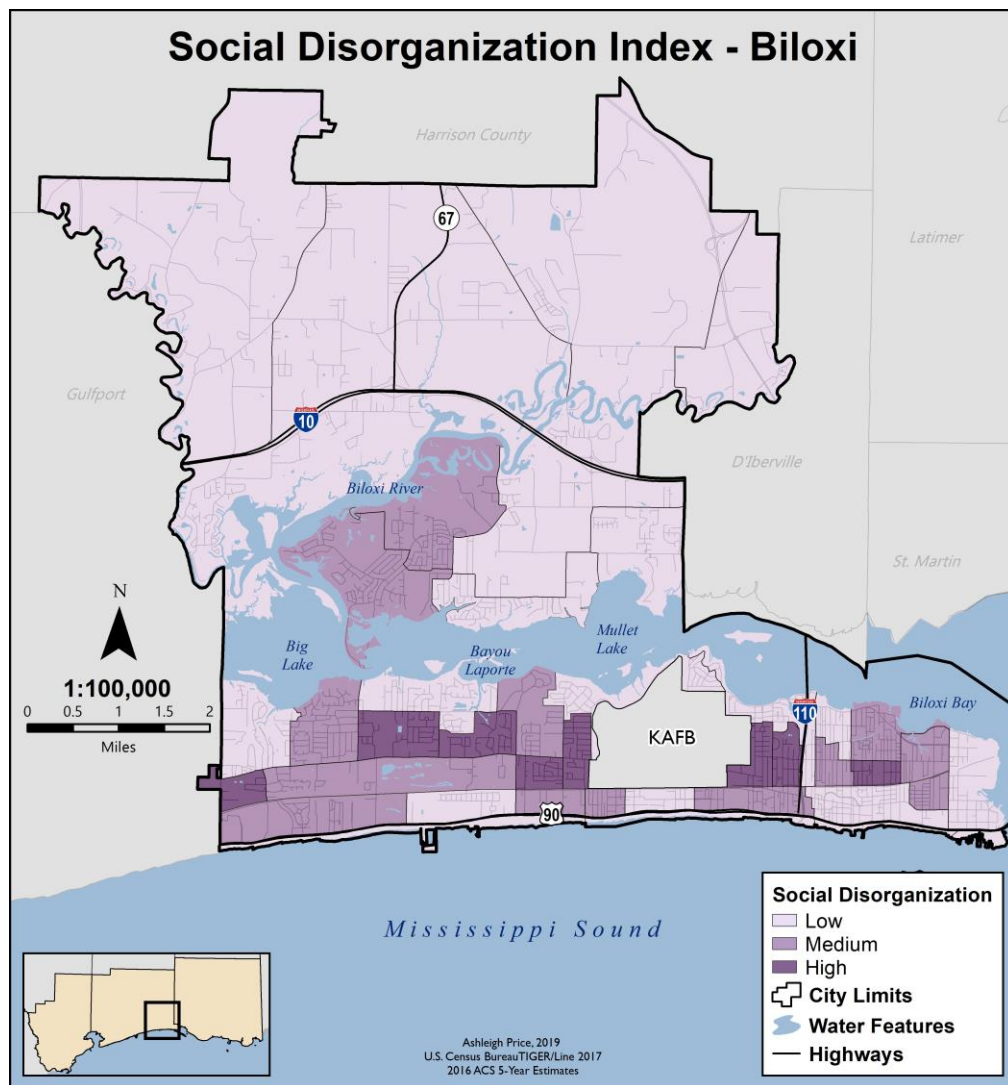


Figure 33. Biloxi Social Disorganization Index

D'Iberville and St. Martin

Figure 34 shows the spatial distribution of disorganized neighborhoods in D'Iberville and St. Martin. Social disorganization occurs in 6 block groups near the I-10 and I-110 corridors. These neighborhoods have small minority populations (33.7%) but moderate racial heterogeneity (HI = 0.48). There is some residential instability as renter occupied households are 44.4% of the total and 46.9% of households moved within the last five years. The average poverty rate is comparatively low at 15%, although 23.3% of households receive food stamps. High school completion rates are high, but 23.0% of the population works in service occupations. LII values range from 0.71 to 1.44, indicating that mean income varies significantly between adjacent block groups.

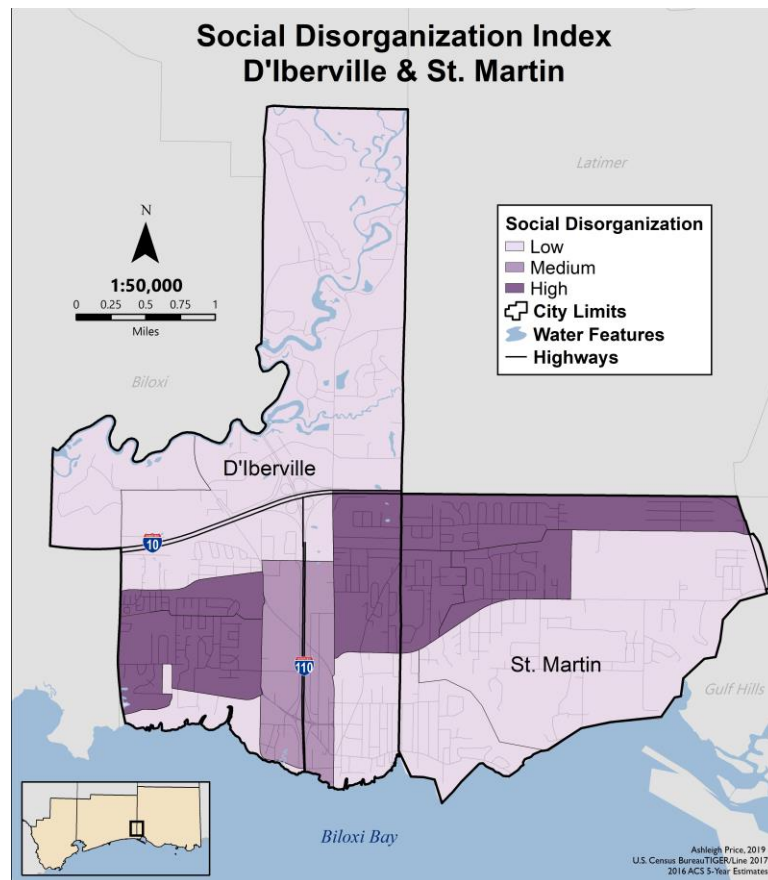


Figure 34. D'Iberville and St. Martin Social Disorganization Index

Ocean Springs

Figure 35 shows social disorganization in Ocean Springs. There are two disorganized block groups in the area south of Highway 90. Female-headed households are 25.2% of the total, 8.5% are single parent households, and 10.9% receive food stamps. The poverty rate is relatively low at 10.9%. Racial minorities are 32.2% of the total population and there is no Hispanic population. Renter occupancy rates are moderate (38.1%) and 42.1% of households moved in 2010 or later. Mean income here exceeds \$53,000, but the LII value is 1.39. Social disorganization here results from moderate levels of economic inequality, driven by a six-figure mean income in a nearby block group.

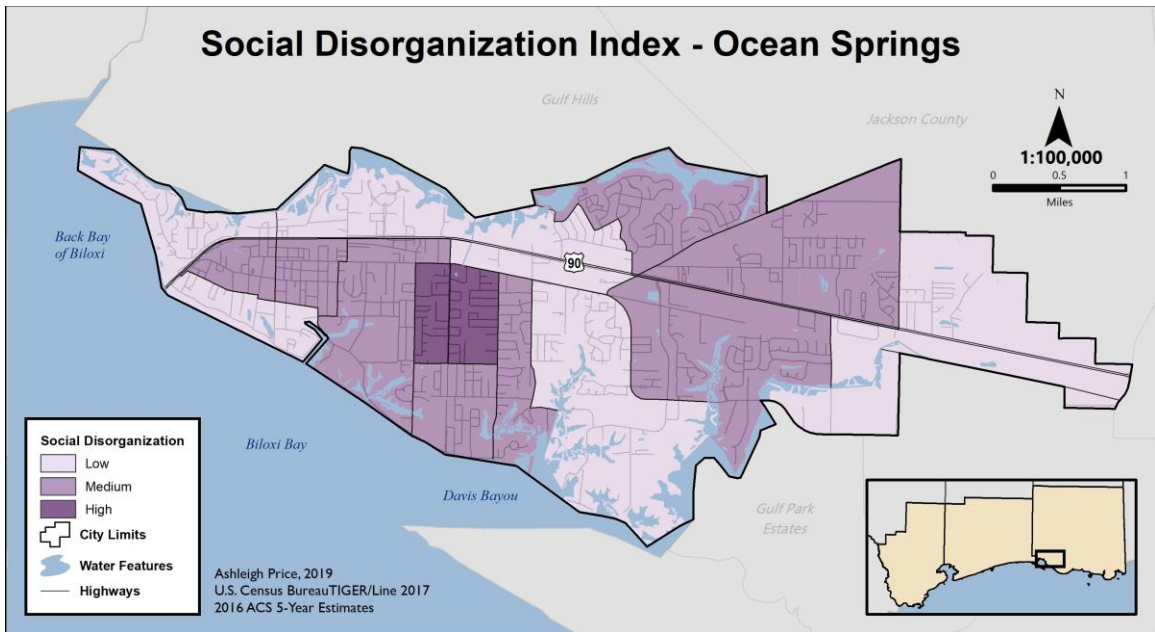


Figure 35. Ocean Springs Social Disorganization Index

Gautier

Social disorganization near Shepard State Park in Gautier results from a prevalence of all 15 indicators (Figure 37). Student apartments near the MGCCC Jackson County campus likely influence the socioeconomic characteristics of the block group. Of the total households, 47.4% live below the poverty line, greater than 45% are female-headed or single-parent, and 65.8% receive food stamps. Residential instability is high as 76.8% households moved within the last five years and 65.5% of homes are renter occupied. African Americans comprise 53.2% of the total population. Ethnic heterogeneity is high (HI = 0.48) as 42.5% of residents are Hispanic.

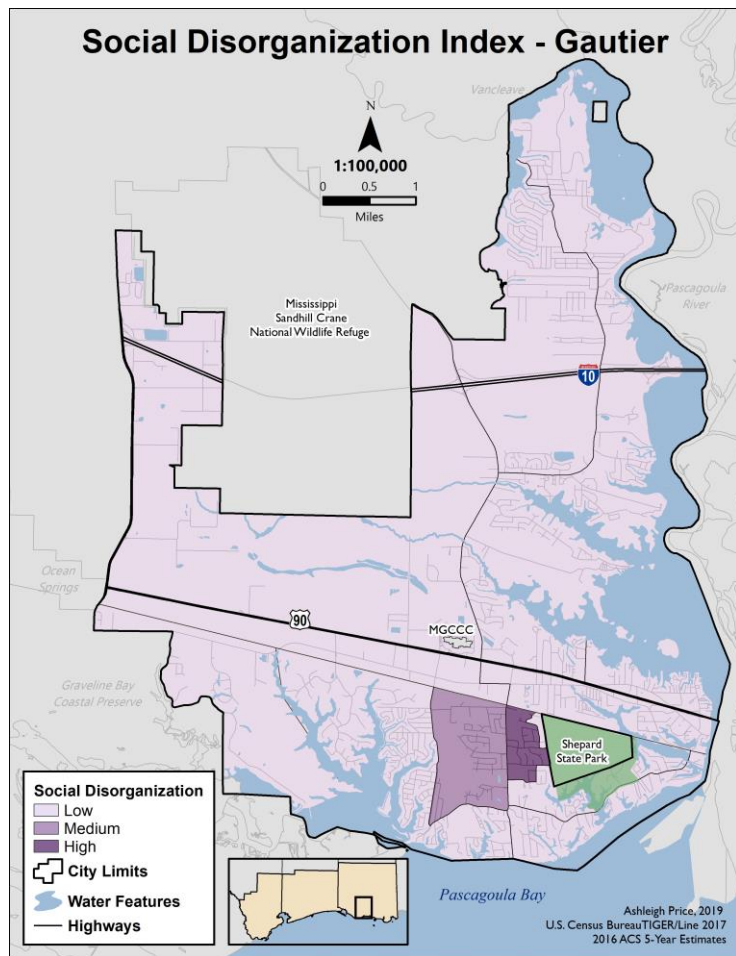


Figure 37. Gautier Social Disorganization Index

Moss Point

Social disorganization in Moss Point is present in three block groups north of Highway 90 (Figure 38). Of the total households, 25.6% are female-headed, but less than 8% are single parent. The poverty rate is 29.4% and income inequality is low (LII = 1.03). High school completion rates are better than the state average and 13.3% of employed people work in service occupations. A large minority population and residential instability contribute to social disorganization in this area. Racial heterogeneity is low (HI = 0.07) because 96.0% of the population is African American. Renter occupied homes are 37.6% of the total and 39.8% of residents moved after 2010.

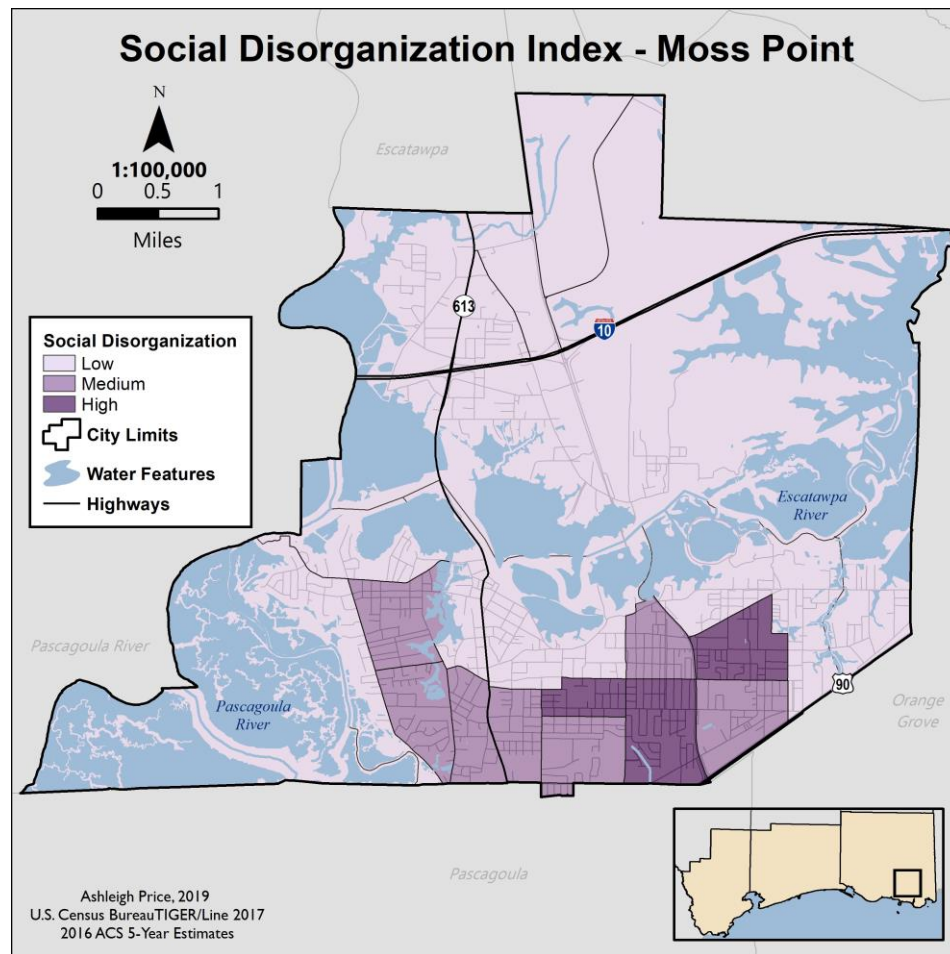


Figure 38. Moss Point Social Disorganization Index

Pascagoula

Figure 39 shows disorganized neighborhoods in Pascagoula. Concentrated disadvantage and residential instability contribute to social disorganization around Pascagoula High School (PHS). The neighborhoods here have a prevalence of female-headed (31.6%) and single-parent (20.1%) households. Renter occupied homes are 56.6% of the total and 41.6% of residents moved within the last five years.

Social disorganization is present around the Lakeside Naval Support Facility (LNSF) on Chicot Avenue. Residential instability is high as 48.9% of households are renter-occupied, and 51.3% have moved in 2010 or later. The poverty rate of 17.4% is on par with the county averages, although 26.7% of households receive food stamps. The presence of a military facility is unlikely to impact the neighborhood socioeconomic characteristics, as less than 1% of permanent residents are active duty military members.

The block group bordering Pascagoula Bay has a prevalence of single parent households (24.6%), although only 13.5% are female-headed. The poverty rate is 28.7% and 28.5% of households receive food stamps. Racial heterogeneity is high (HI = 0.61), and 32.6% of the population is African American. Residential instability results from the presence of several apartment complexes. Renter occupied households are 47.9% of the total and 49.0% of residents moved within the previous five years.

Social disorganization around Cherokee Elementary School (CES) results from economic inequality. Although high school completion rates are high and only 11.4% of employed persons work in service occupations, the poverty rate is 48.45%. Income inequality (LII=1.74) results from a mean income three times higher in neighboring block groups.

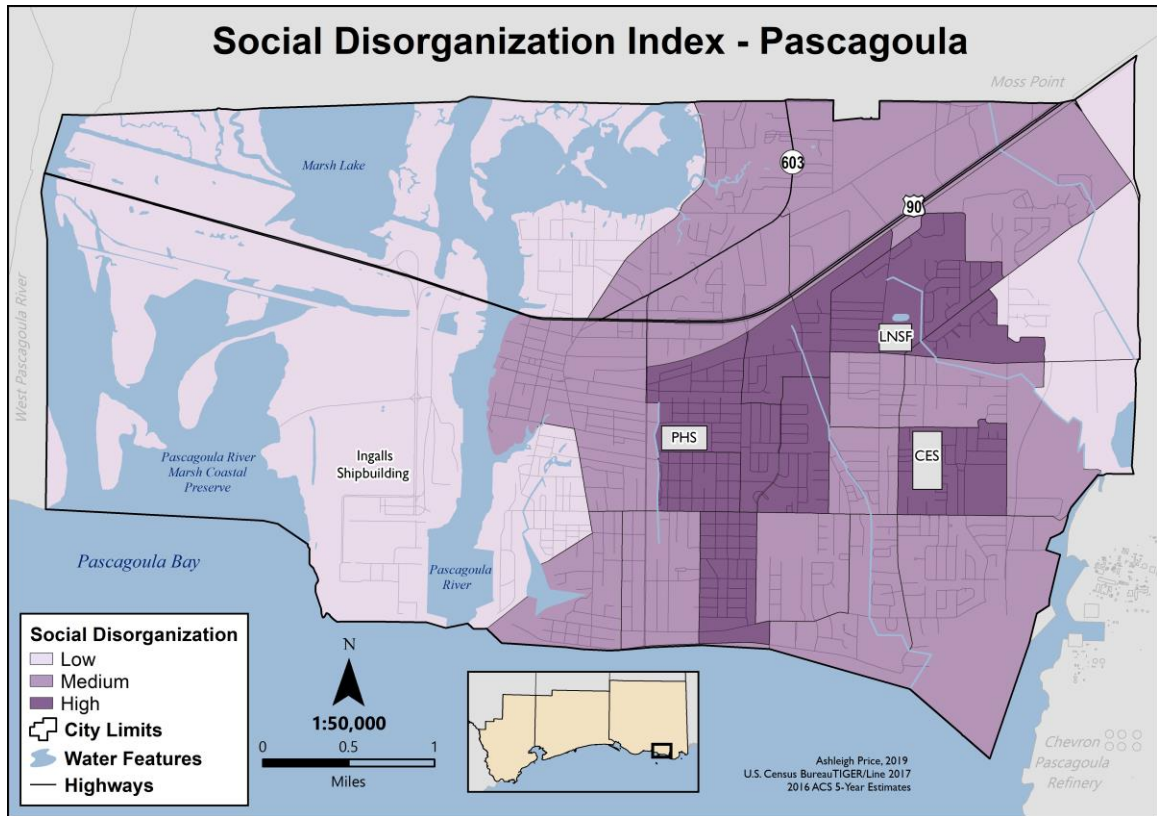


Figure 39. Pascagoula Social Disorganization Index

Hazus-MH Models

To match the scale of the socioeconomic data, the damage estimates and the total residential square footage were dissolved to the block group. To account for possible spurious precision in the damage estimates, “affected” block groups are considered to have at least 0.1% damage. Table 9 shows the descriptive statistics for each of three model results in the affected block groups. As expected, hurricane winds impact the entire study area, while flooding is present in fewer block groups.

Table 9

Descriptive Statistics for Block-Group Level Hazus-MH Damage Estimates

Statistic	Hurricane	Riverine	Coastal
Affected Block Groups	264	91	30
Maximum	78.83%	49.48%	0.50%
Minimum	0.23%	0.10%	0.11%
Mean	31.34%	3.31%	0.21%
Standard Deviation	23.04%	6.06%	0.11%

Block-group level damage estimates for the percent of residential square footage with “At Least Moderate” damage

This research used Jenks classification of the Hazus damage estimates to identify the most at-risk areas. Table 10 details the residential damage intervals for each of the three models. Figures 40, 41, and 42 show the spatial distribution of the damage estimates using Jenks classification.

Table 10

Hazus-MH Residential Damage Estimates, Jenks Classification

Residential Damage	Hurricane	Riverine	Coastal
Low	0.23% - 18.75% (93)	0.0% - 4.71% (249)	0.0% (234)
Medium	18.76 % - 46.53% (97)	4.72 % - 20.67% (14)	0.01 % - 0.23% (22)
High	> 46.53 % (74)	> 20.67% (1)	> 0.23 % (8)

Low, medium, and high residential damage estimates for the Hazus-MH model results, Jenks Classification. The number of block groups in each class are shown in parentheses.

Hazus returned hurricane loss estimates for the entire study area (Figure 40). Damage ranges from 0.23% to 78.8%. The highest damage estimates (> 46.5%) are in neighborhoods along the coast in Harrison and Jackson Counties. Damage is low in 93 block groups in both the rural and urban portions of the study area.

Riverine flood damage estimates are present in 91 block groups (Figure 41). In Harrison County, damage is minimal along the Wolf River (3.5%), the Little Biloxi River (.54%), and the Back Bay of Biloxi (4.1%). In northern Gulfport and Biloxi, damage along the Biloxi River ranges from 8.0% to 9.1%. Residential damage is moderate (13.2%) surrounding the southward flowing reach of the Tchoutacabouffa River, near the Jackson County line. South of Bernard Bayou in Gulfport, the damage estimate is 20.1%. In northern Jackson County, flood damage is minimal (1.5%) around Black Creek, and slightly higher (8.5%) near the Pascagoula River. Flooding along the Escatawpa River produced damage in parts of Helena (13.1%) and in eastern Moss Point (10.7%). The maximum riverine damage (49.48%) is in Hancock County along the Jordan River.

The coastal flood model returned damage in 30 of 264 block groups (Figure 42). Damage estimates from the coastal flood model are generally low and show little variation throughout the study area. This is unsurprising, as residential development in coastal flood zones is typically mitigated to NFIP regulations. The largest percent of residential damage in the study area occurs in Hancock County, west of Bay St. Louis in the Shoreline Park community (0.50%), outside of Waveland around Bayside Park (0.41%), and in the rural area around the Jordan River between Kiln and Diamondhead (0.37%).

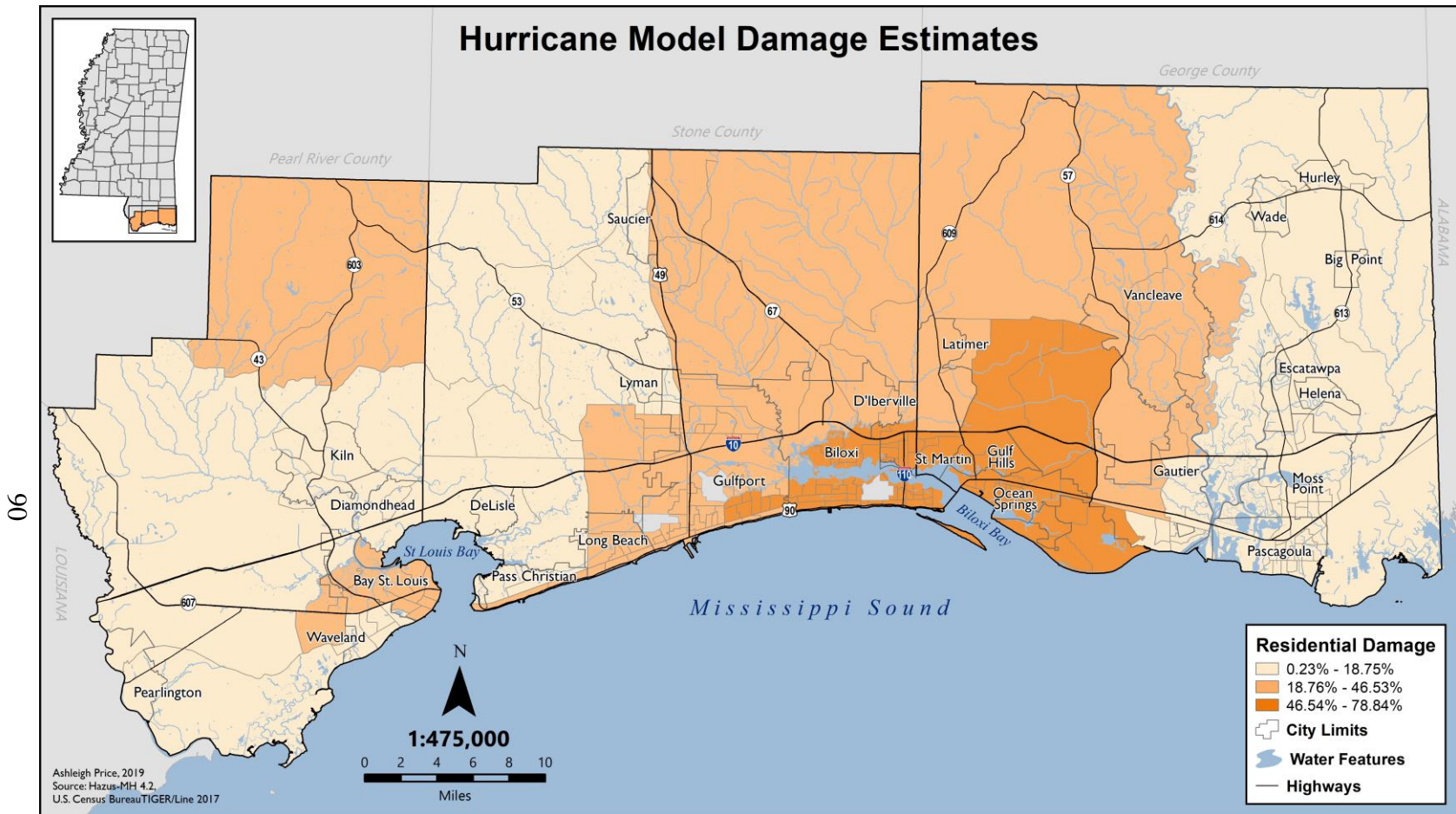


Figure 40. Hurricane Model Damage Estimates, Block Groups

Hazus-MH hurricane model residential damage estimates aggregated to block groups, Jenks Classification. Percentages are the proportion of residential square footage with “At Least Moderate” damage

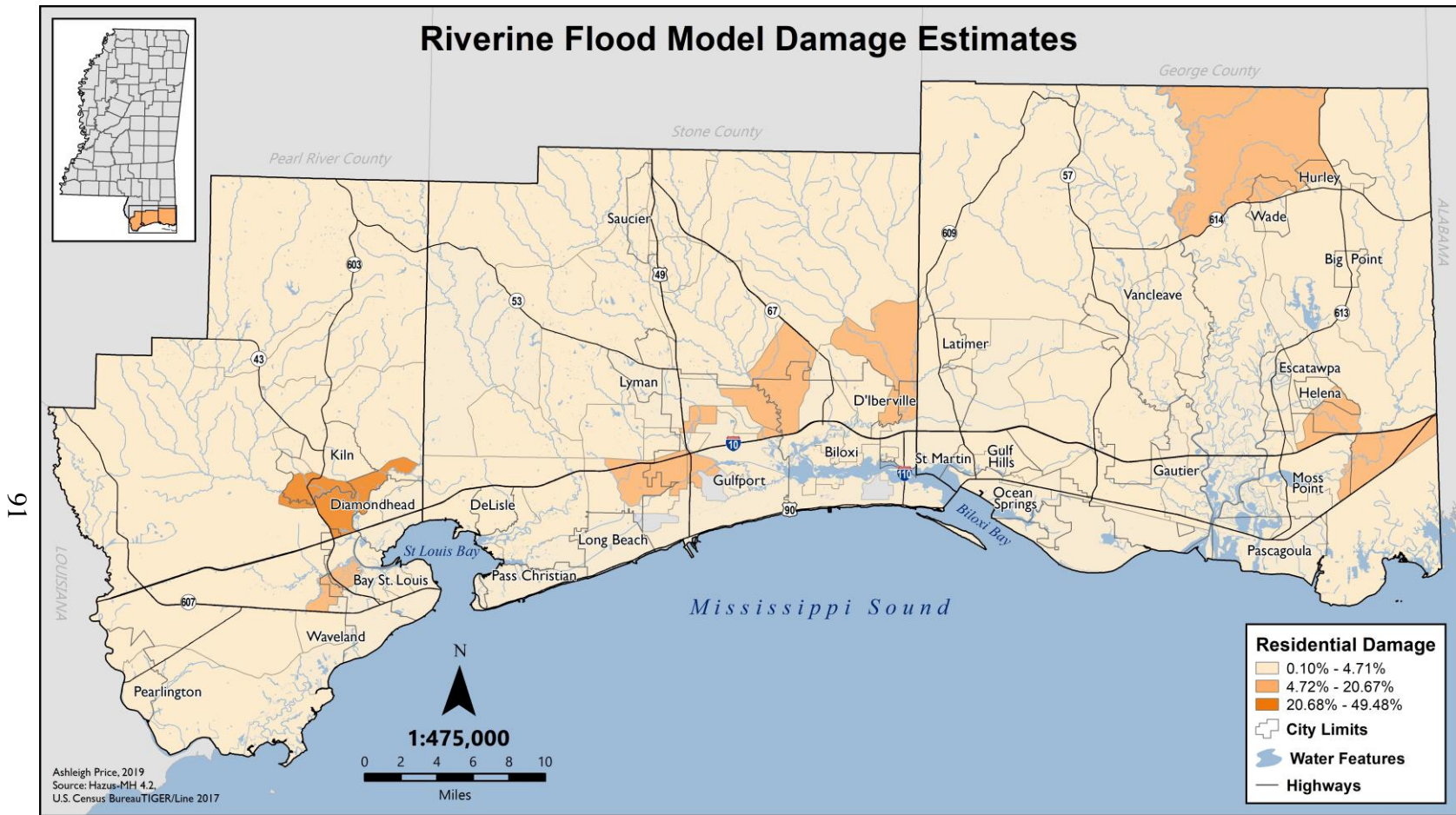


Figure 41. Riverine Model Damage Estimates, Block Groups

Hazus-MH hurricane model residential damage estimates aggregated to block groups, Jenks Classification. Percentages are the proportion of residential square footage with “At Least Moderate” damage

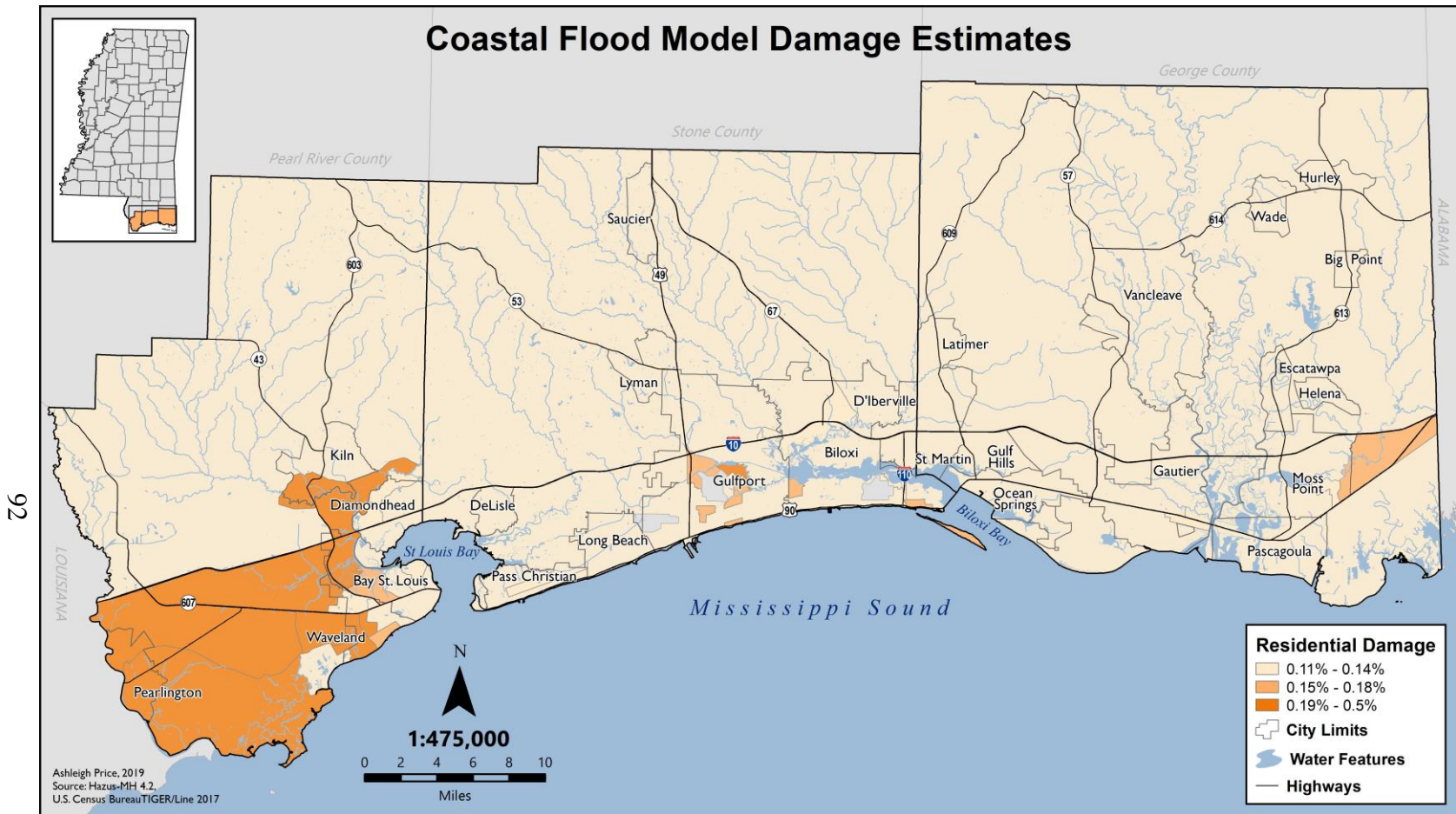


Figure 42. Coastal Flood Model Damage Estimates, Block Groups

Hazus-MH coastal flood model residential damage estimates aggregated to block groups, Jenks Classification. Percentages are the proportion of residential square footage with “At Least Moderate” damage

Offender Support Services

There are nine categories of offender support services: Probation and Parole Offices, Food and Clothing, Criminal Justice, Education and Life Skills, Employment, Health, Public Libraries, Shelter, and Substance Abuse Treatment. Food and clothing providers include faith-based organizations, food pantries, and thrift stores. The criminal justice category is the local police departments. The education and life skills category includes local organizations such as Families First for Mississippi (FFFM) that provide GED preparation, career counseling, and basic adult education. Shelters include domestic violence refuges and day shelters. Substance abuse treatment includes inpatient and outpatient service providers. The health category includes community health centers, free clinics, and mental health providers. Of particular interest is the availability of support services within each county and the travel distance to local community supervision offices. Supervision conditions can prevent offenders from traveling outside their county of residence and travel to area community supervision offices presents significant challenges for offenders without access to a personal vehicle. Table 11 details the number of services by category in each of the three counties.

The MDOC Hancock County Probation and Parole Office is in Bay St. Louis. There are no shelters or treatment centers in Hancock County but there are health services available in Bay St. Louis. There are no employment agencies although there are five public libraries with computers available for public use. The Hancock County Library System also provides free life skills classes and tax preparation (HCLS 2019a). The FFFM in Bay St. Louis provides parenting, life skills, workplace training, and anger

management classes (FFFM 2018). Regarding food and clothing, the local Goodwill is in Waveland and the Hancock County Food Pantry is in Bay St. Louis.

The Harrison County Probation and Parole Offices are in Gulfport and Biloxi, an average of 3.67 Manhattan miles from disorganized neighborhoods. There are community health centers throughout the county. Mental health services are available in Gulfport and Biloxi, and there is a substance abuse treatment center in Gulfport. The day shelter and women's domestic violence center are both in Biloxi. The Harrison County Library System has seven public libraries with public computer access and routinely offers free community events (HCLS 2019b). The FFFM centers in Gulfport and Biloxi provide life skills classes and a computer lab for client use (FFFM 2018). There are eight food and clothing providers in Gulfport and Biloxi including two faith-based organizations, food pantries, and Salvation Army and Goodwill stores.

The Jackson County Probation and Parole Office is in Pascagoula, meaning offenders in Gautier and St. Martin must travel a significant distance to meet with their community supervision officer. There are community health centers in Pascagoula, Moss Point, and Vancleave. The food pantries in Jackson County are in Pascagoula and Ocean Springs. The day shelter is in Moss Point and the women's domestic violence center is in Pascagoula. A faith-based, inpatient, substance abuse treatment facility is in Vancelave. The free clinic is in Ocean Springs and the local health department is in Pascagoula. The FFFM center in Moss Point provides life skills and childcare classes (FFFM 2018). The Jackson George Regional Library System has seven locations, each providing community events and computer access (JGRLS 2019).

Table 11

Offender Support Service Availability by County

	Hancock	Harrison	Jackson	Total
Health	2	23	7	32
Food & Clothing	2	8	3	13
Criminal Justice	2	8	5	15
Education & Life Skills	1	5	1	7
Employment	0	3	1	4
Public Libraries	5	7	5	17
Substance Abuse Treatment	0	1	1	2
Shelter	0	3	3	6
Probation & Parole Office	1	2	1	4

Offender support services by type and county (FMS, MSSP 2018)

Crime Rates

This research asked whether disorganized neighborhoods have a higher instance of criminal activity. Block group level data was available for seven FBI Uniform Crime Report (UCR) offenses: murder, robbery, assault, sexual assault, burglary, larceny, and motor vehicle theft. Figures 43-49 show the spatial distribution of each crime type using Jenks classification.

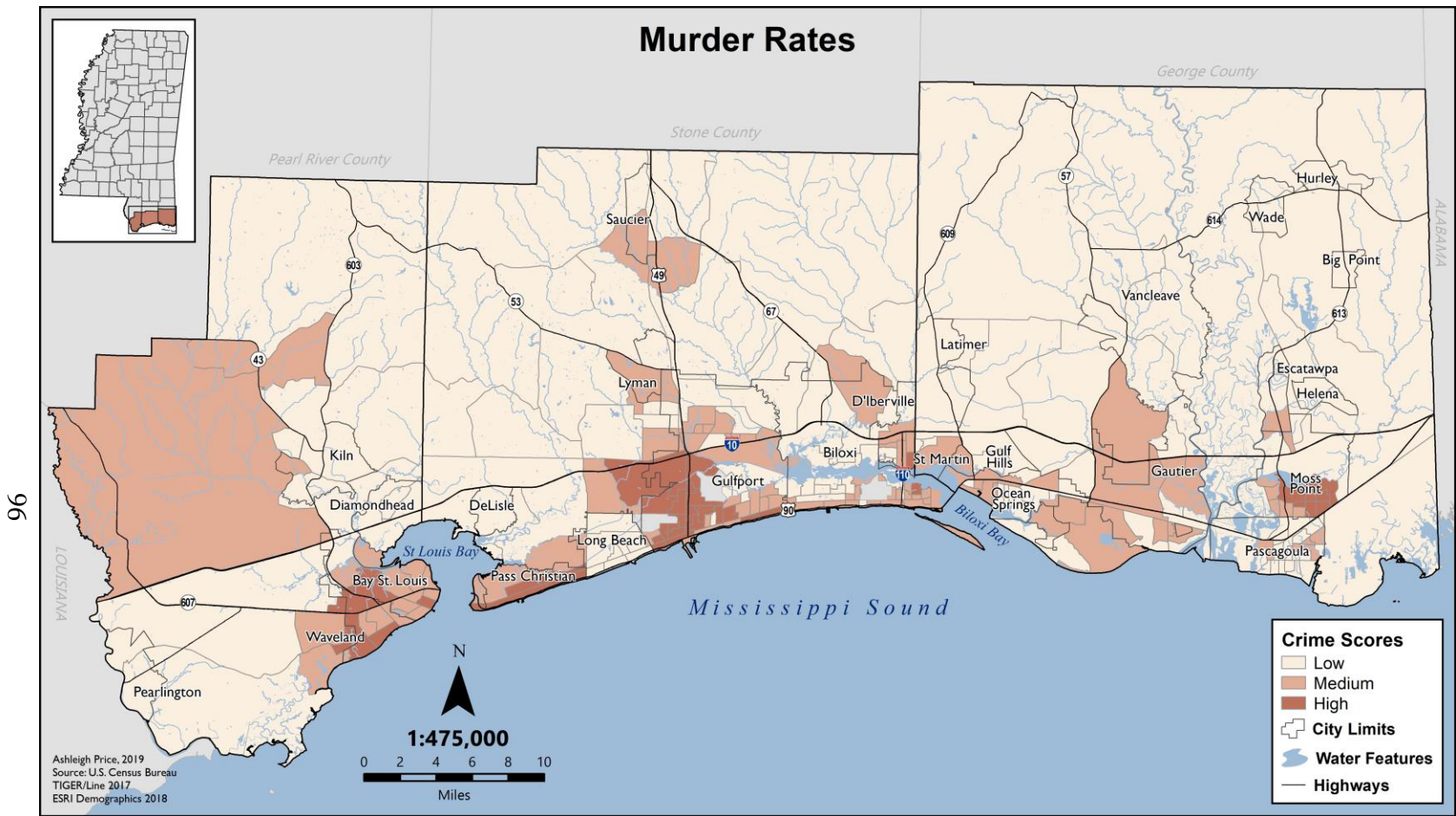


Figure 43. Study Area Murder Rates

Block -group level murder rates, Jenks Classification (ESRI Demographics 2018).

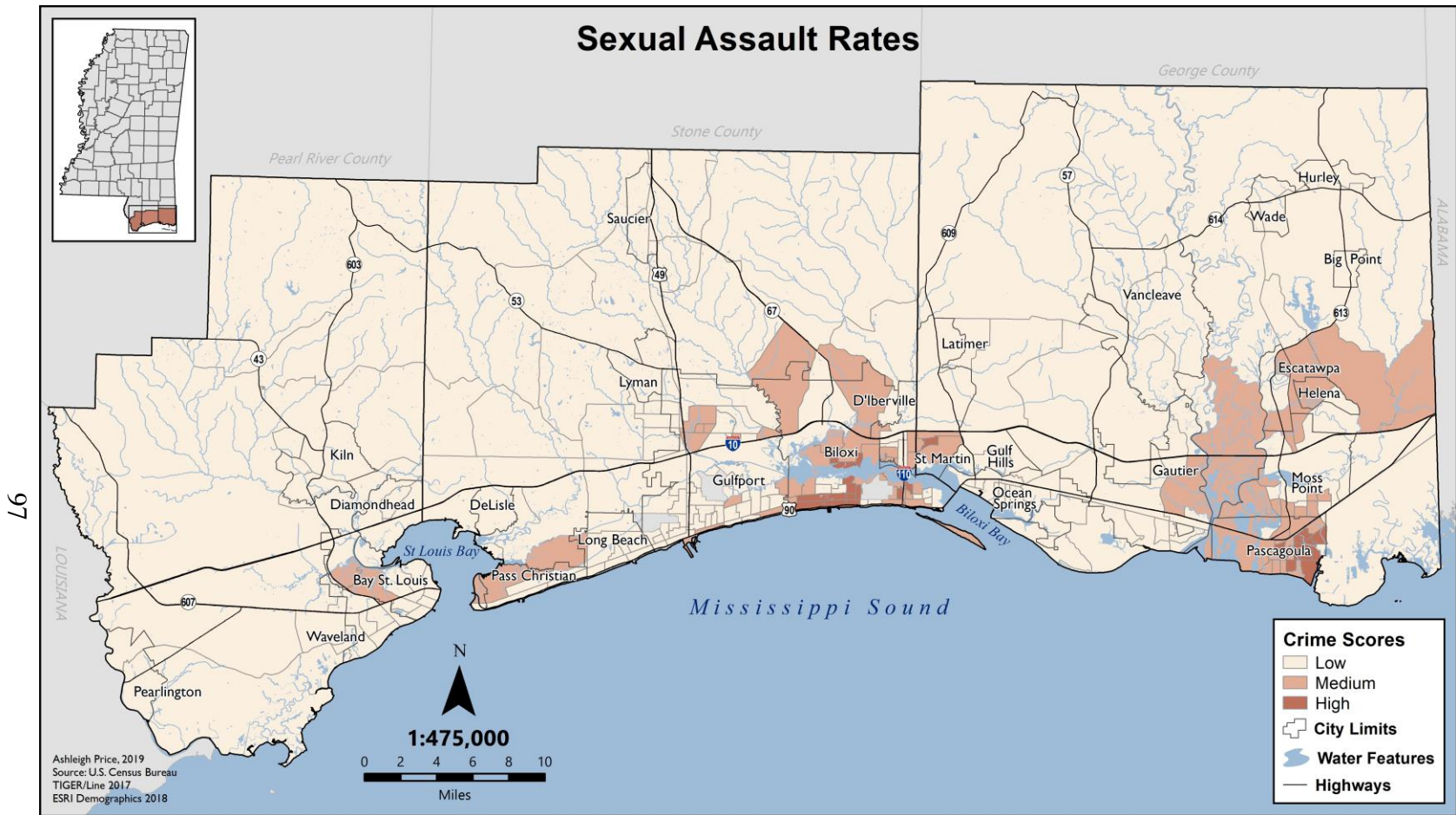


Figure 44. Study Area Sexual Assault Rates

Block -group level sexual assault rates, Jenks Classification (ESRI Demographics 2018).

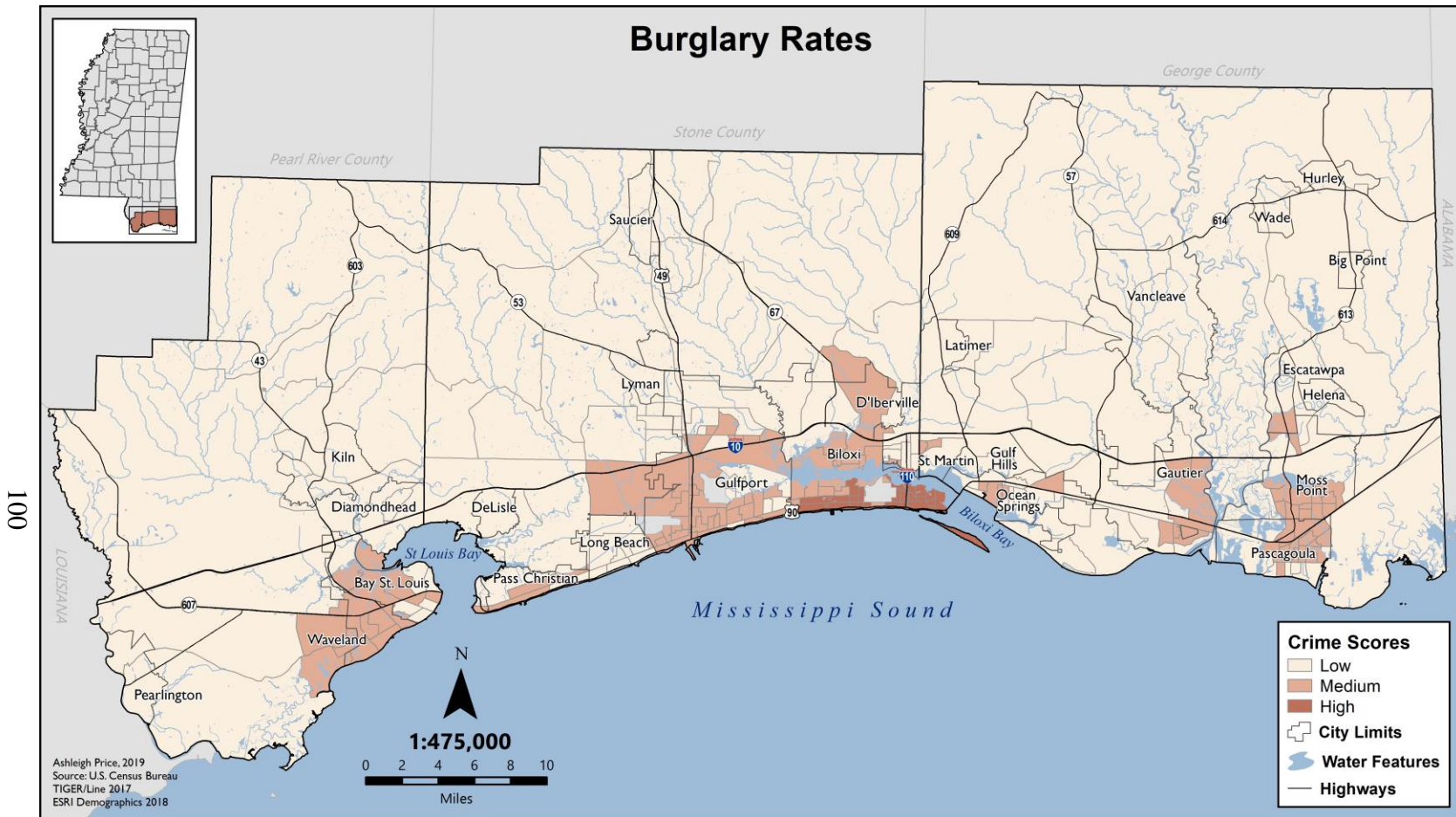


Figure 47. Study Area Burglary Rates

Block -group level burglary rates, Jenks Classification (ESRI Demographics 2018).

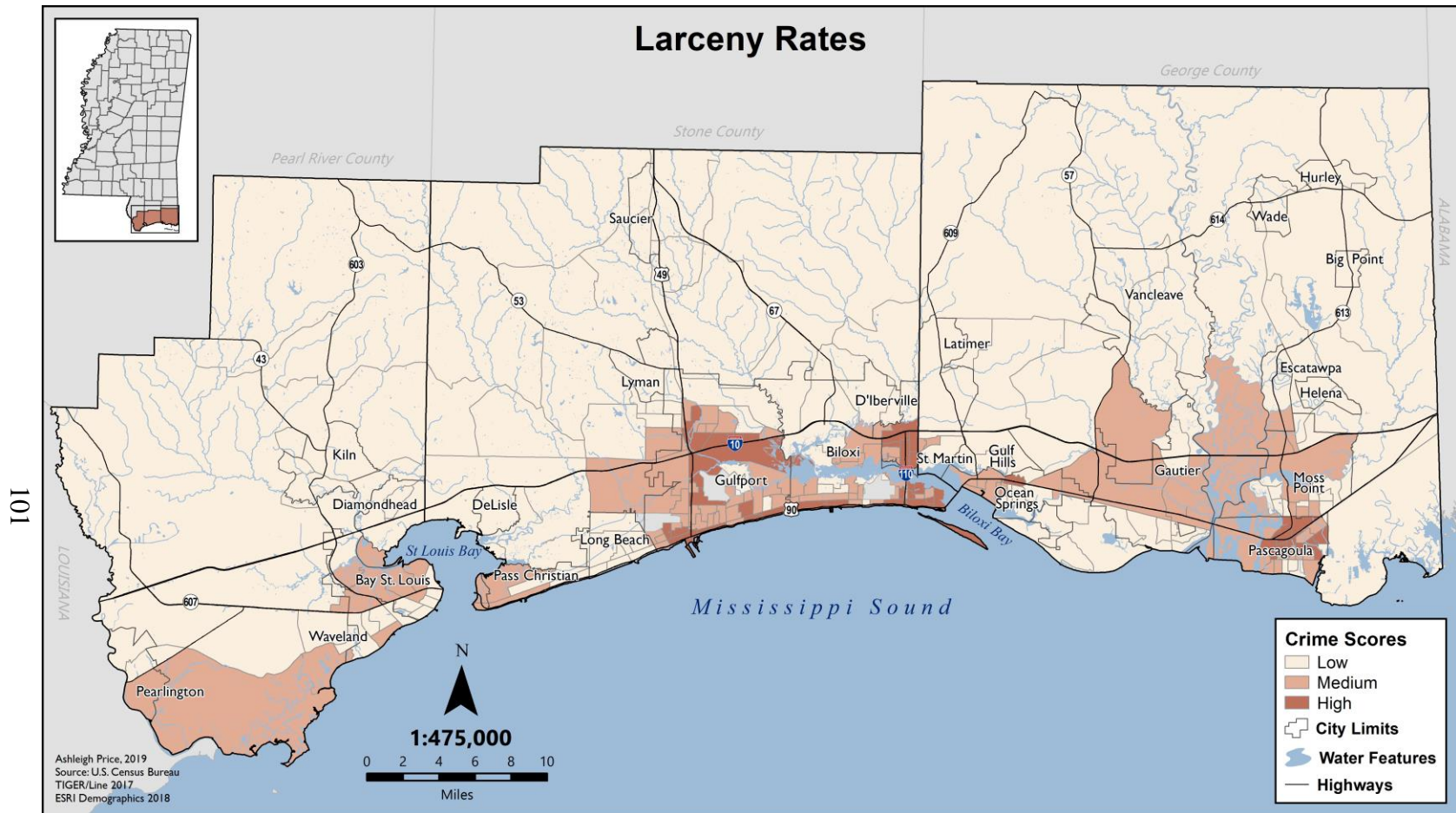


Figure 48. Study Area Larceny Rates

Block -group level larceny rates, Jenks Classification (ESRI Demographics 2018).

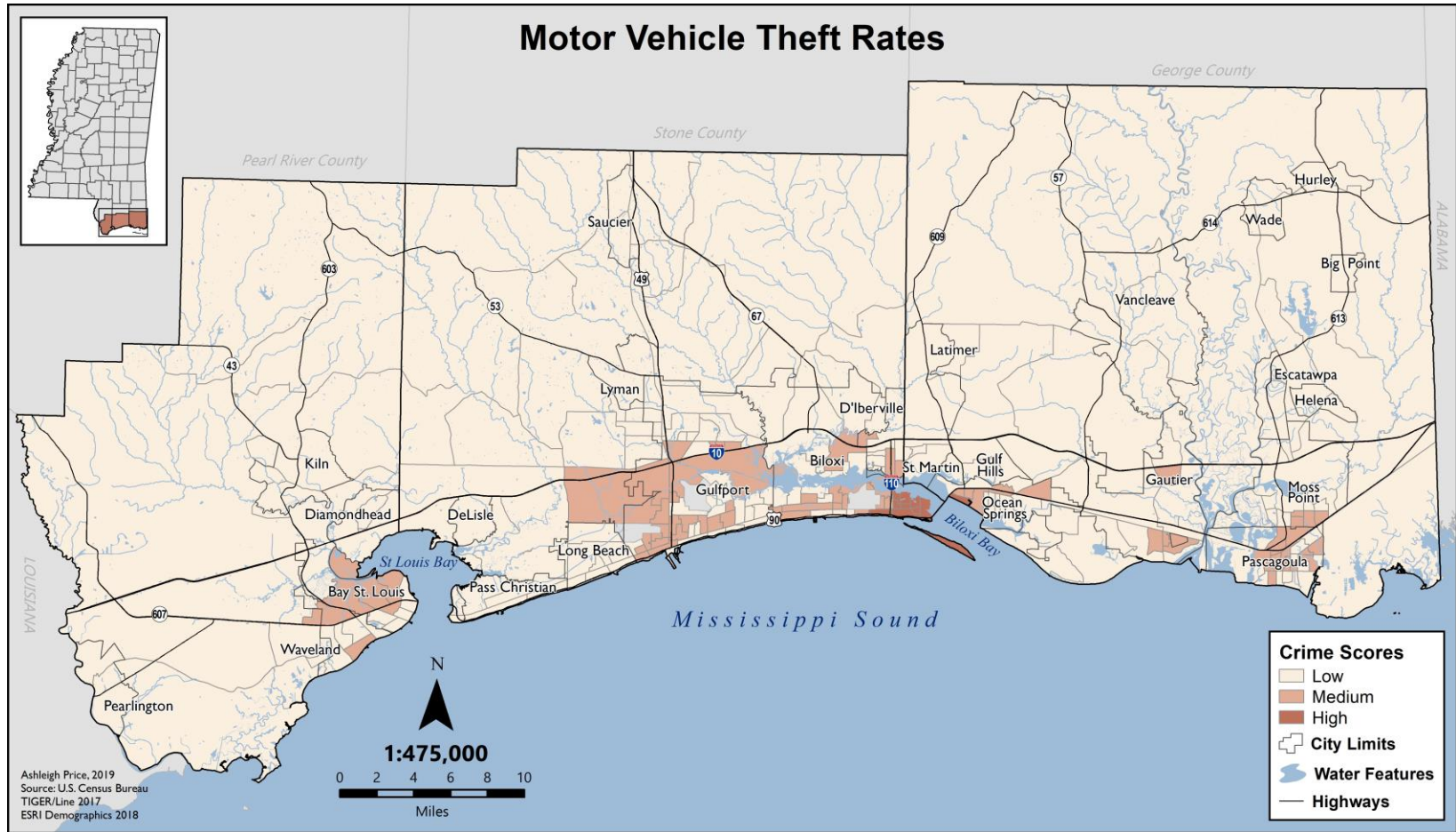


Figure 49. Study Area Motor Vehicle Theft Rates

Block -group level murder motor vehicle theft, Jenks Classification (ESRI Demographics 2018).

Spatial Relationships

Social Disorganization and Hazard Vulnerability

A primary goal for this research was to measure whether offenders tend to live in areas at risk from coastal hazards. Pearson's correlation tested the Social Disorganization Index (SDI) for bivariate relationships with the Hazus damage estimates. The results show the SDI has a small inverse relationship with coastal ($r = -0.18$) and riverine flooding ($r = -0.20$), and a small, positive ($r = 0.22$) relationship to hurricane damage.

Flood risk is negligible in most of the disorganized neighborhoods in the study area. Most block groups show minimal or nonexistent coastal damage estimates, although four neighborhoods are at moderate risk. Riverine damage estimates are missing or insignificant in all but one disorganized neighborhood. In northern Gulfport, around the Flat Branch distributary of the Bernard Bayou, riverine damage is moderate. Low hurricane damage is present in 12 block groups, 10 are at moderate risk, and 19 disorganized neighborhoods are at high risk. Table 12 details the affected population. Figures 50 - 52 display the SDI and damage estimates on a bivariate choropleth map.

Table 12

Coastal Hazards - Affected Population in Disorganized Neighborhoods

	Hurricane	Riverine	Coastal
Low	14,246	51,525	48,467
Medium	12,664	2,883	5,941
High	27,498	0	0

Affected population in disorganized neighborhoods for each damage class.

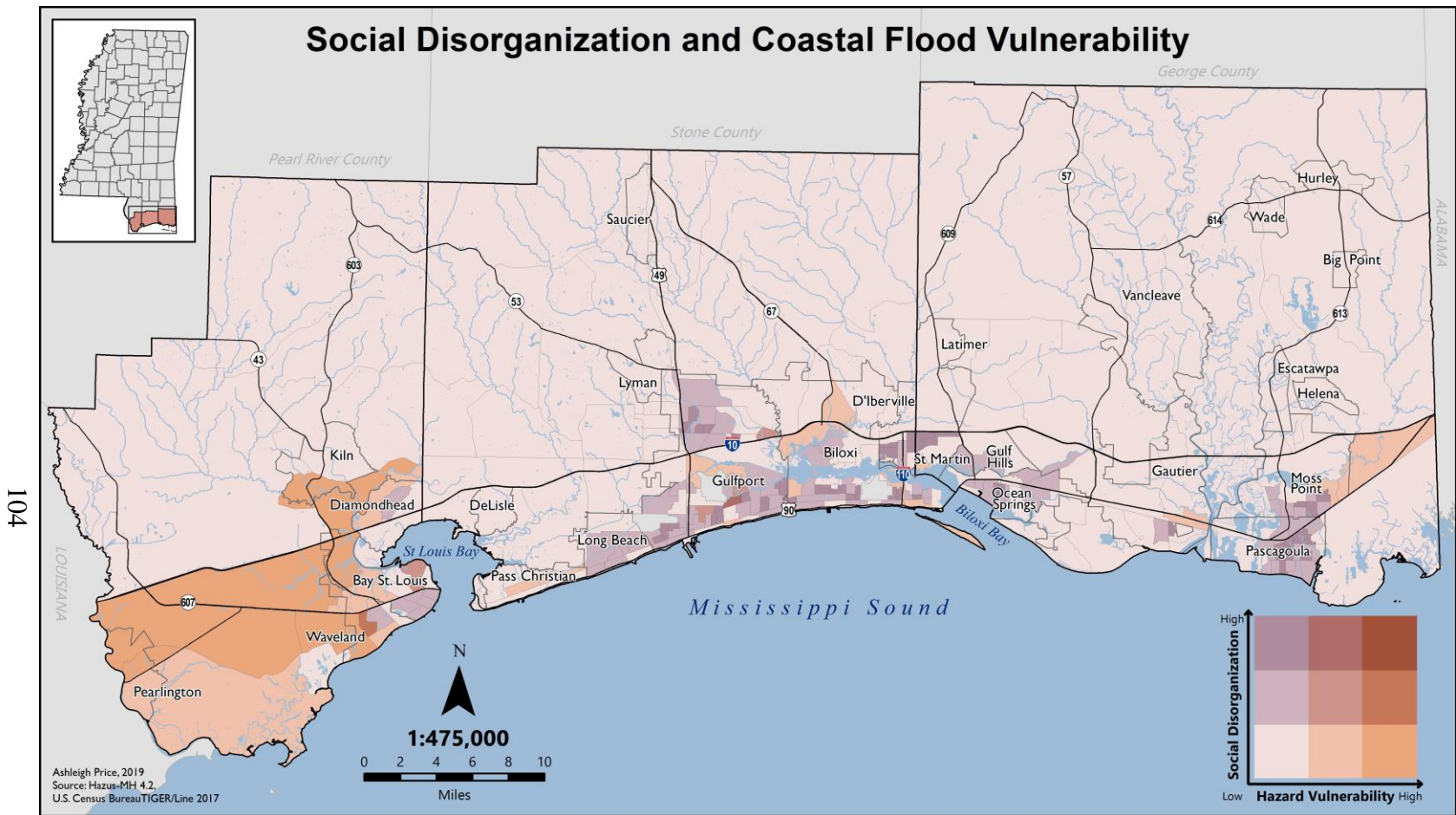


Figure 50. Bivariate Choropleth Map, SDI and Coastal Damage Estimates

Bivariate choropleth map of the Social Disorganization Index (SDI) and Coastal Damage Estimates, Jenks classification.

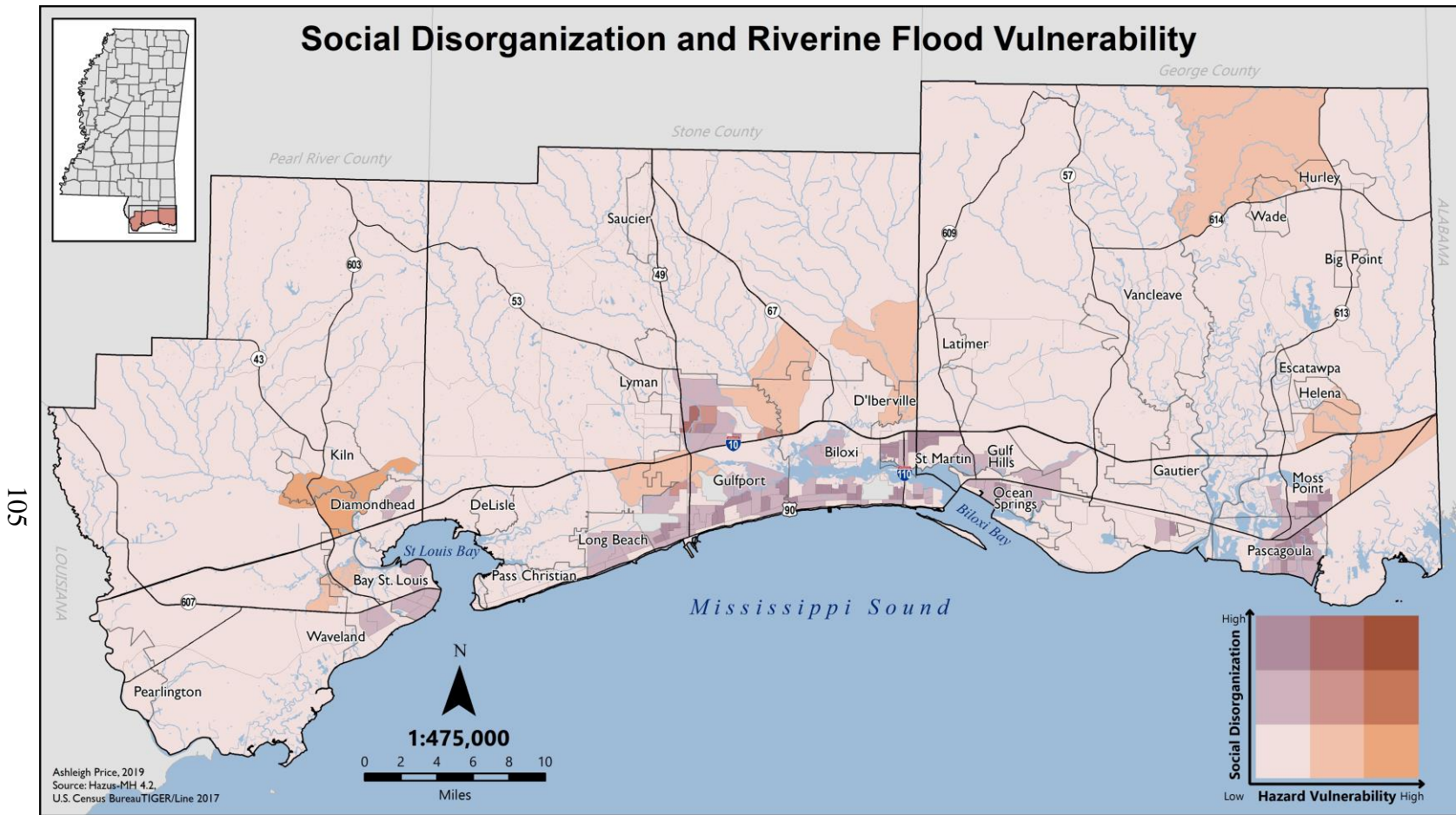


Figure 51. Bivariate Choropleth Map, SDI and Riverine Damage Estimates

Bivariate choropleth map of the Social Disorganization Index (SDI) and Riverine Damage Estimates, Jenks classification.

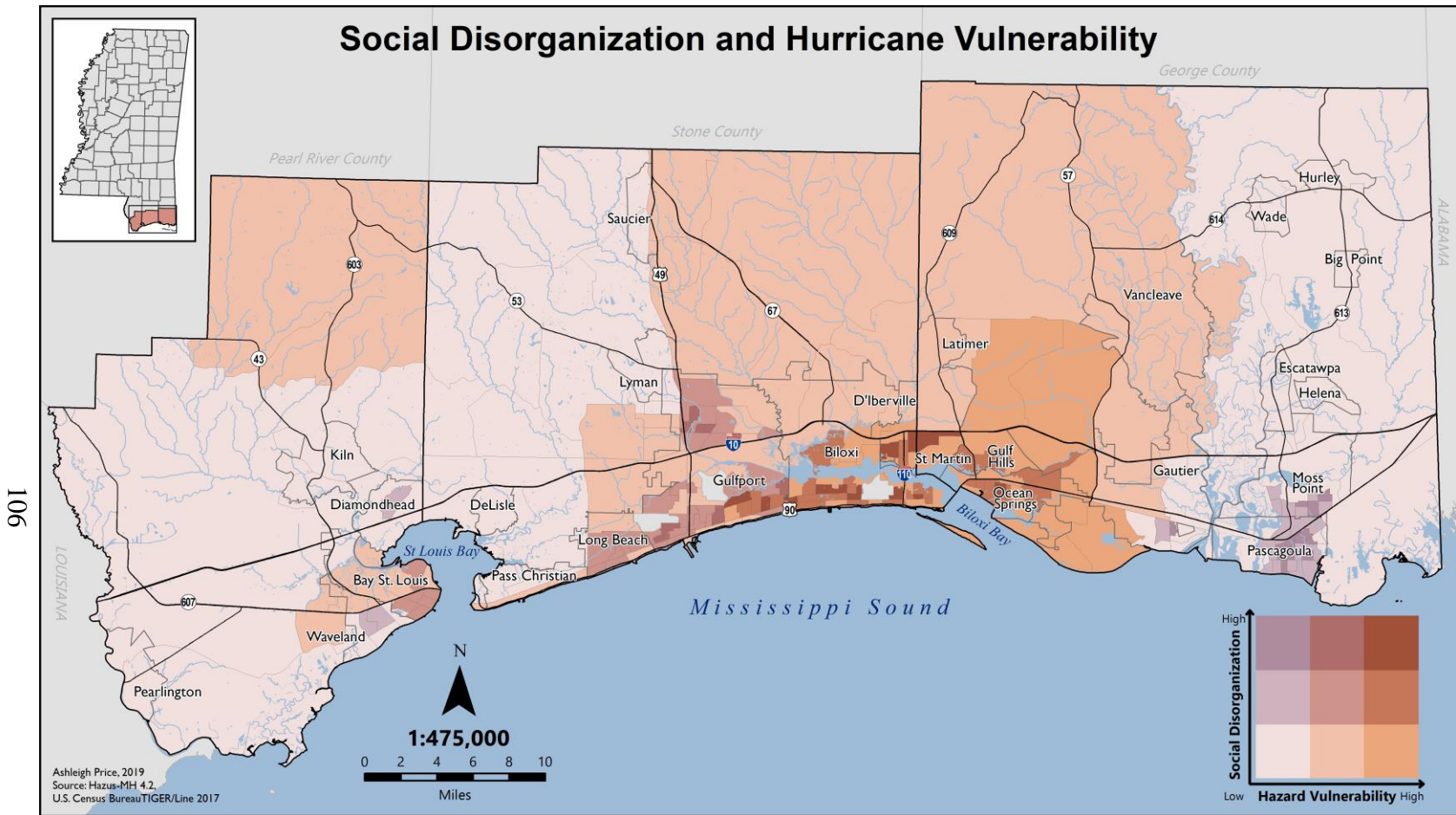


Figure 52. Bivariate Choropleth Map, SDI and Hurricane Damage Estimates

Bivariate choropleth map of the Social Disorganization Index (SDI) and Hurricane Damage Estimates, Jenks classification.

Social Disorganization and Neighborhood Crime Rates

Pearson's correlation tested the Social Disorganization Index (SDI) for bivariate relationships with each of the UCR offenses. Table 13 shows the detailed results including correlation coefficients, t-test statistics, and associated p-values for each crime type. Figures 53-59 display the SDI and crime rates on a bivariate choropleth map. At the tri-county scale, the SDI is moderately related to rates of sexual assault, burglary, and larceny and there is a small relationship to rates of murder, robbery, assault, and motor vehicle theft.

Table 13 *Social Disorganization and Neighborhood Crime - Pearson's Correlation*

Offense Type	Pearson's Correlation (<i>r</i>)	t-test Statistic	p-value
Murder	0.16	2.57	0.011027
Sexual Assault	0.39	6.89	<.00001
Robbery	0.16	2.68	0.007884
Assault	0.29	4.87	<.00001
Burglary	0.30	5.18	<.00001
Larceny	0.30	5.07	<.00001
Motor Vehicle Theft	0.13	2.21	0.28178

Results of Pearson's correlation tests for the Social Disorganization Index (SDI) and seven crime types.

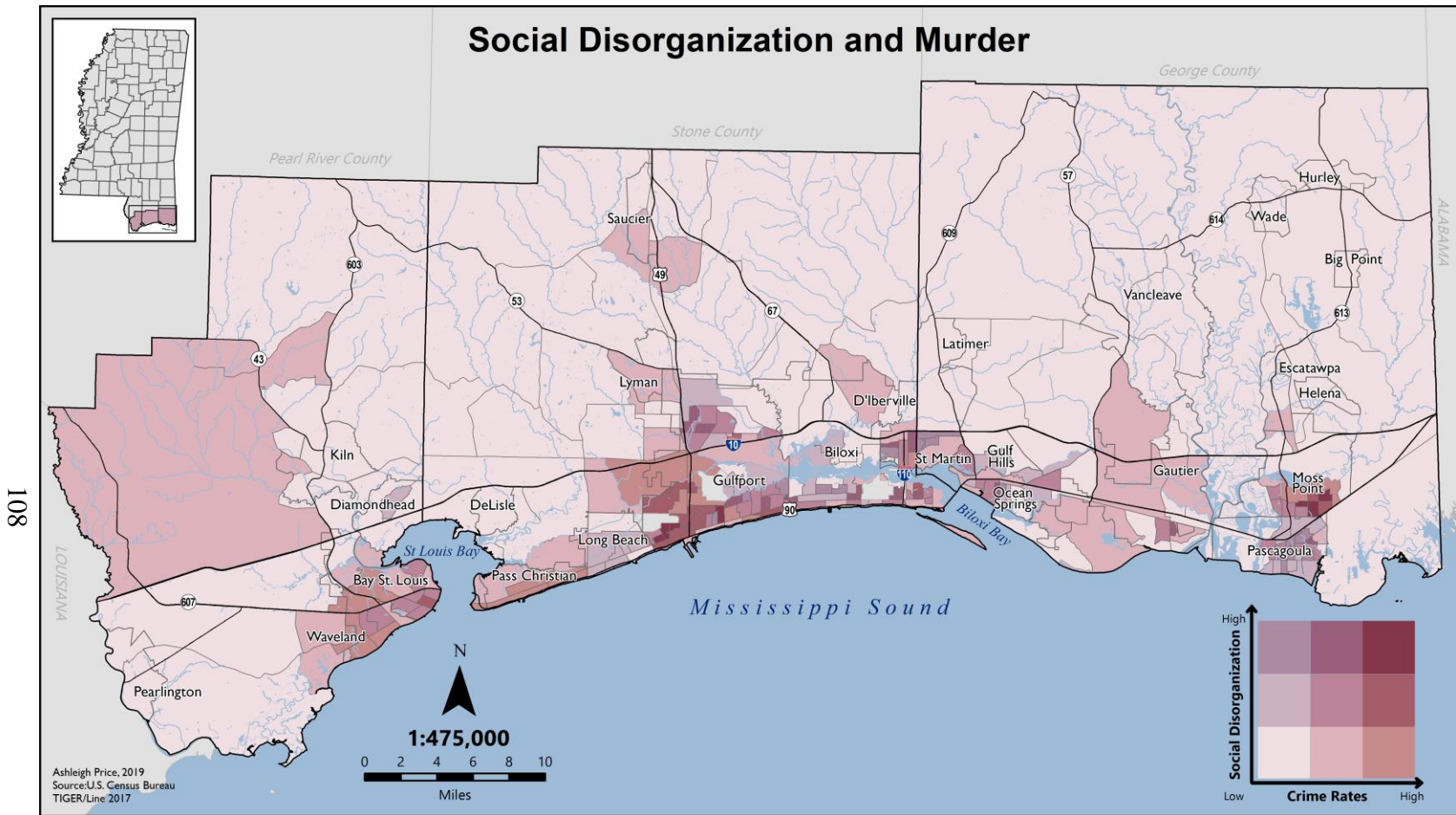


Figure 53. Bivariate Choropleth Map, SDI and Murder Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and murder rates, Jenks classification.



Figure 54. Bivariate Choropleth Map, SDI and Sexual Assault Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and sexual assault rates, Jenks classification.

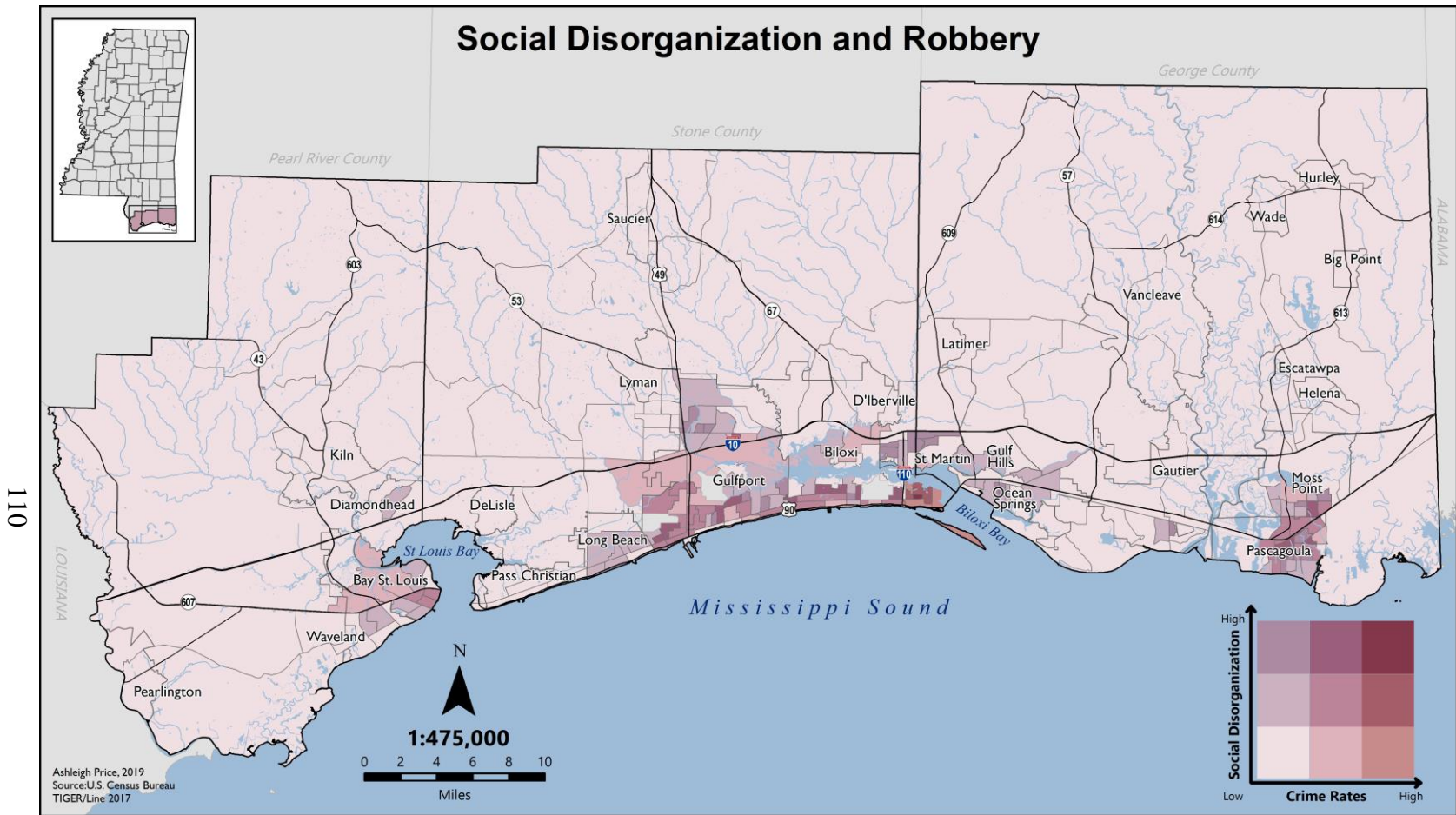


Figure 55. Bivariate Choropleth Map, SDI and Robbery Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and robbery rates, Jenks classification.

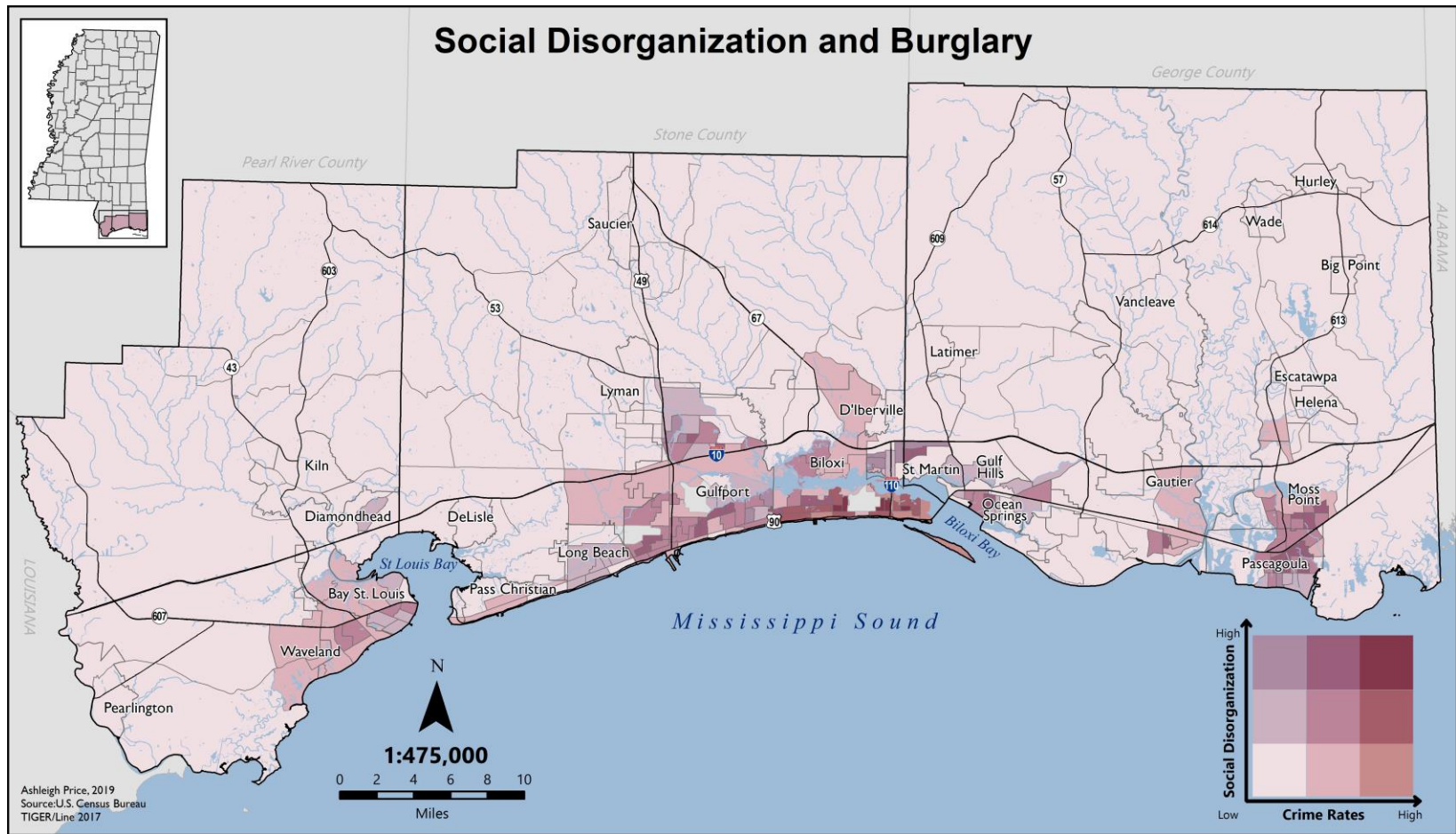


Figure 57. Bivariate Choropleth Map, SDI and Burglary Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and burglary rates, Jenks classification.

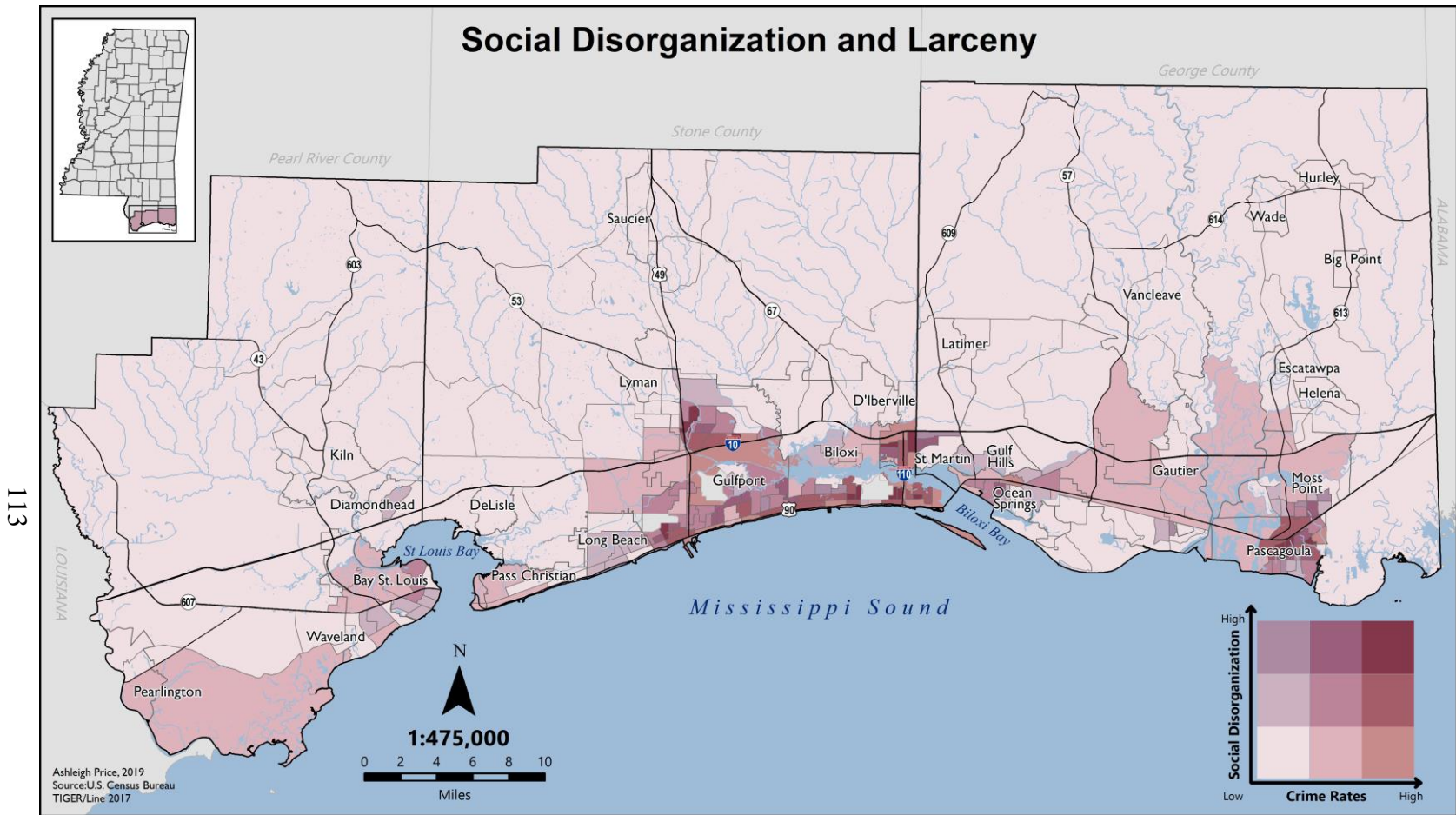


Figure 58. Bivariate Choropleth Map, SDI and Larceny Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and larceny rates, Jenks classification.

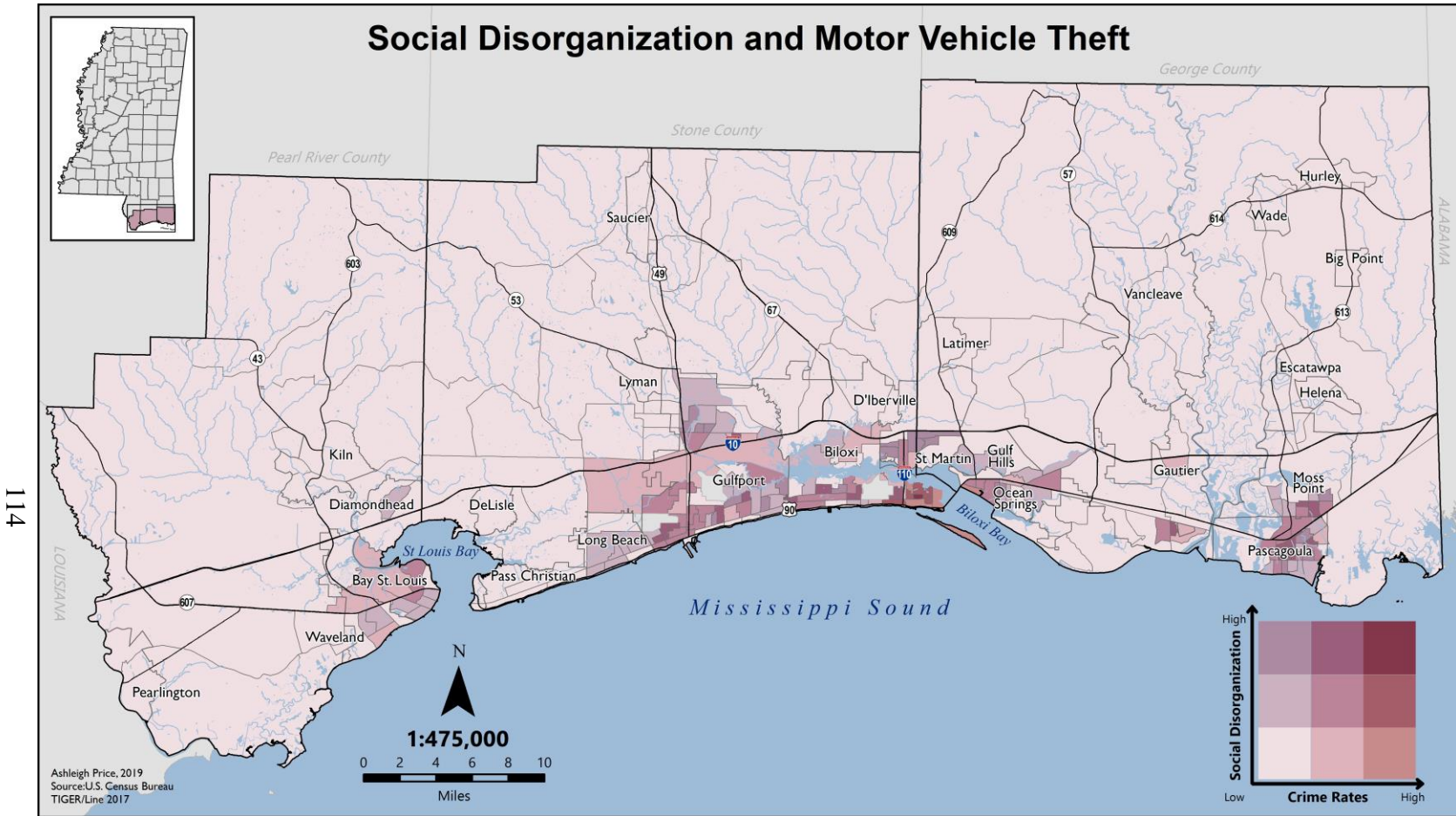


Figure 59. Bivariate Choropleth Map, SDI and Motor Vehicle Theft Rates

Bivariate choropleth map of the Social Disorganization Index (SDI) and motor vehicle theft, Jenks classification.

CHAPTER VI – DISCUSSION AND CONCLUSIONS

Overview

This chapter first discusses the results presented in the previous chapter and provides the conclusions and implications of this research. The second section acknowledges the limitations to this project. Finally, this chapter describes the avenues of future research resulting from this thesis.

Discussion

Assessing a group's unique vulnerability to hazards is an established paradigm in human geography. The heart of geographical vulnerability research is the concept that hazardous events disproportionately impact certain individuals and communities. The social vulnerability literature has identified numerous marginalized groups with unique impediments to recovery, including minorities and those with reduced socioeconomic status. External factors, such as biased development and long-term societal ostracization, often place these communities in the most-at risk areas.

This study highlights the unique vulnerability of the offender population. Offenders have reduced socioeconomic status and live in marginalized neighborhoods. The conditions of probation and parole may exacerbate limited opportunity by imposing mobility restrictions. During a hazard event, offenders have legal considerations regarding their evacuation. Mapping social disorganization as a proxy for offender residential patterns is thus useful to both emergency management and community corrections operations.

The spatial and social disparities in vulnerability and resilience have important implications for emergency management. This research has shown that disorganized

communities are home to socially vulnerable populations. Identifying disadvantaged neighborhoods helps officials develop community-specific risk reduction strategies. In areas with reduced socioeconomic conditions, the homes may need structural mitigation and residents often lack the resources to recover from a hazardous event. For residents with mobility limitations, emergency managers can employ localized evacuation assistance. In culturally diverse neighborhoods, residents may have a language barrier or unique risk perception that impacts the effectiveness of crisis communication. Mapping ethnic heterogeneity shows emergency managers where to develop targeted risk communication plans. Hazard modeling helps emergency managers predict local hazard conditions and develop specialized mitigation strategies for underprivileged communities.

Understanding offender vulnerability has significant applications for community corrections operations. Poverty, race, reduced social capital, lack of gainful employment, and living in an underserved neighborhood all contribute to increased vulnerability, reduced resilience, and a greater likelihood of recidivism. This means addressing hazard vulnerability may also lead to more positive reentry outcomes.

The first goal of this research was to document how the supervision conditions change during a state of emergency. In regard to state-supervised offenders, this information was not available during the timeline of this research. The United States Probation and Pretrial Services office in Gulfport provides a publicly available EOP for federal probationers. The federal supervision conditions require offenders to provide the address of a friend or family member who may temporally provide shelter. During an evacuation, offenders must report their new location to their supervising officer within 24

hours, even if they are subject to electronic monitoring. Should that officer prove unavailable, the offender must report their presence to the closest federal probation office. The federal EOP also states violent and sex offenders must notify local law enforcement and emergency shelter management of their arrival (MSSP 2018a).

This project sought to identify offender residential patterns using the socioeconomic characteristics of social disorganization. Principal component analysis (PCA) created the Social Disorganization Index (SDI) for block groups in the study area. The results identified 41 disorganized neighborhoods where offenders are likely to reside. These communities occur exclusively in the coastal cities and exhibit reduced socioeconomic conditions.

This research next identified the areas most at-risk from coastal hazards and examined general trends in the relationship of social disorganization to physically vulnerable areas. Hazus-MH hurricane wind and coastal and riverine flood models estimated residential damage for the 100-year return period. There is some relationship to the level of social disorganization and hurricane damage in the study area. This is primarily because hurricane damage is greatest in the coastal areas, although there is little variation in risk throughout the study area. Burton (2010) found similar results when modeling the effects of Hurricane Katrina in coastal Mississippi, although this is primarily due to the scale of analysis. Hurricane wind speeds, and thus modeled damage estimates, are unlikely to vary significantly within the tri-county area.

Several authors have shown disadvantaged populations are disproportionately at risk from flooding. Ueland and Warf (2006) found minorities in the US south tend to live near riverine floodplains, but outside of coastal flood zones. Walker and Burningham

(2010) showed women and those living in poverty suffer more adverse health risks and take longer to recover from floods. Sayers, Penning-Rowsell, and Horritt (2018) showed flood risk is geographically isolated to disadvantaged communities in both coastal cities and rural areas. The results of the present study show mixed agreement with the extant literature, instead finding that disorganized neighborhoods are at a lower risk of floods, at least along the Mississippi Gulf Coast. This divergence from the literature can best be explained by local flood zone regulations and development patterns.

Comparison of SDI and flood damage estimates reveals there is little risk from coastal or riverine flooding in disorganized neighborhoods. Generally, there is a negative relationship between coastal flood risk and social disorganization. The NFIP regulations require structures in the coastal flood zone to be elevated above the 100-year stillwater elevation, protecting waterfront property from damage during 1% annual chance flood events. Ueland and Warf (2006) showed that minorities tend to live outside the coastal flood zone, as the lowest lying residential areas are also the most desirable. In beachfront communities like those of the Mississippi Gulf Coast, underprivileged populations are unlikely to reside in waterfront neighborhoods.

Comparison of the SDI to riverine damage estimates also shows an inverse relationship. Primarily, the NFIP regulations prevent encroachment of residential property into the 100-year floodplain, meaning damage is minimal during 1% annual chance events. Disorganized neighborhoods in coastal Mississippi are located near the coast, but riverine flood damage is possible throughout the study area, meaning urban populations are not at disproportionate risk. Regarding local development, riverfront neighborhoods in coastal Mississippi are often home to wealthier populations.

This research next asked whether disorganized neighborhoods have a higher instance of reported criminal activity. The crux of community supervision standards is the fact that most offenders recidivate. Routine activity theory states offenders more often pursue the nearest criminal opportunity. Relating social disorganization to neighborhood crime rates can help community supervision officials assess recidivism risk in the offender population. More importantly, offenders who live in criminogenic neighborhoods are likely to become victims themselves.

Pearson's correlation of the SDI and seven crime types produced mixed results. At the tri-county scale, the SDI is moderately related to rates of sexual assault, burglary, and larceny, and has a small relationship to murder, robbery, assault, and motor vehicle theft. Generally, this means crime rates increase with social disorganization, although the spatial distribution of the SDI and local development patterns explain most of the variation in these relationships. Several latent factors outside the scope of this research also influence neighborhood crime rates. Land use type, the level of police activity, or the presence of illegal markets can all effect criminal activity.

Disorganized neighborhoods are exclusively in the coastal cities, as are the highest rates of burglary, robbery, and larceny. Property crimes are more ubiquitous in commercial areas and the highest rates in the study area occur in developed areas near the coast. At the tri-county scale, the proportion of commercial property in a block group strongly relates to an increase in total property crimes. Similarly, the presence of casinos and other crime generators along the waterfront may increase the number of attractive robbery targets. Property crime patterns in coastal Mississippi are most likely a function of development, rather than the presence of nearby residences of offenders.

Motor vehicle theft is the least prevalent of all crime types and the highest rates are in eastern Biloxi. Only one block group in the area exhibits social disorganization, meaning motor vehicle theft likely results from the presence of crime generators, rather than neighborhood characteristics. Casinos along Highway 90 provide criminal opportunity by attracting large numbers of patrons, many of whom will leave their cars unattended for extended periods of time.

Rates of sexual assault have the strongest relationship to social disorganization. Given that most sexual assault goes unreported, it's likely the correlation is much stronger. Female-headed households are a key contributor to the SDI, meaning there are a larger number of potential victims in disorganized neighborhoods. At the tri-county scale, there is no relationship ($r = 0.08$) between rates of sexual assault and the proportion of female-headed households. This suggests female residents of disorganized neighborhoods may be significantly more likely to become victims of sexual assault.

The highest rates of murder and assault are present in both rural and urban areas, limiting the relationship to the SDI. Crime attractors and generators have less influence on murder and assault than property crimes, as violent crime usually results from some existing personal relationship. Regarding neighborhood characteristics, much of the tri-county area has poverty rates above the state average. The criminology literature has continually identified a correlation between poverty and violent crime within numerous study regions and at different spatial scales. Coastal Mississippi is no exception, as poverty has a strong bivariate relationship to murder and assault at the tri-county scale.

This research also examined whether offenders have access to support services within their county of residence. Local libraries can be invaluable to offenders by

providing computer access for employment applications. Fortunately, there are libraries throughout coastal Mississippi, including the rural areas around Saucier, Kiln, and Hurley. Food and clothing resources are slightly less prevalent, requiring offenders to travel to Bay St. Louis, Gulfport, Biloxi, Ocean Springs, or Pascagoula to visit a food pantry or free/reduced cost clothing opportunity. Community supervision conditions often require life skills courses including anger management, parenting, or GED classes. This research revealed few locations for these services, although it is assumed community corrections offices would provide their caseloads with such information.

The conditions of probation and parole require offenders to attend regular meetings with their supervision officer. This research examined the distance to local probation and parole offices from disorganized neighborhoods. The results show offenders are likely to live a significant distance from their supervisory office. On average, offenders do not live within walking distance of the nearest location, leaving them to rely on friends and family or public transportation.

The Coast Transit Authority (CTA) has bus routes throughout Harrison County, providing ample public transportation for residents of disorganized neighborhoods. CTA also provides free transportation to emergency shelters during a hurricane evacuation. While there is a bus route through St. Martin and Ocean Springs, it appears there is no public transportation in Gautier, Moss Point or Pascagoula. Offenders in Jackson County are thus left to rely on friends and family when traveling to supervision meetings, required classes, or support services.

Limitations

This thesis focused on identifying hazardous locations and a socially vulnerable population. In analyzing demographic variables, the scale of analysis is limited to available data. The Modifiable Areal Unit Problem (MAUP) impacts the spatial distribution of socioeconomic variables because descriptive statistics can vary at different spatial units or scales of analysis. This research used data from the US Census Bureau 2016 block-group level ACS estimates, meaning the scale of analysis is limited to the enumeration unit. Similarly, geographic phenomena are not confined to geopolitical boundaries. This research considered the three counties of the Mississippi Gulf Coast. Conducting this analysis with different aggregation levels or within a different study region may produce variation in the results.

Block-group level crime data was taken from ESRI demographics and uses statistics from the FBI Uniform Crime Reports (UCR). For incidents to be included in the UCR measure, the victim must report it to the authorities and that law enforcement agency must participate in the UCR program. Criminologists routinely acknowledge the “Dark Figure of Crime” as the discrepancy between the number of crimes that occur and those that are reported. The dark figure of crime decreases with the seriousness of the offense, meaning the proportion of reported incidents for some crimes (e.g. murder) is higher than others (e.g. property crimes). The block-group level crime indices are useful for comparative purposes within the study region, as finer scale crime analysis was outside the timeline and focus of this research.

Due to numerous logistical and ethical limitations, communication with offenders was outside the scope of this research. Community supervision officers are the primary

source of information regarding offender responsibilities both routinely and during a disaster. Proposed primary data collection was in-person interviews with community supervision agents. The University gave IRB approval (Appendix E) and a detailed research application was submitted to the Mississippi Department of Corrections. MDOC was ultimately unable to fulfill this request within the timeline of the research.

Future Research

Community supervision officers have routine interactions with their caseloads and an amicable offender/officer relationship leads to better reentry outcomes. It is possible this relationship could lead to positive resilience outcomes. For risk communication, officers may become trusted information sources for preparedness information such as maintaining shelter in place kits. Future research will investigate how the offender-officer relationship and relates to offender resilience and recovery.

Successful reentry is more likely for offenders who use social services and participate in community organizations. It is unclear which services and organizations offenders utilize, and to what degree. This is important to understand, as these types of services could also offer resources during a disaster. Future research will survey probationers and parolees to determine the local services they use and follow up with those services to discuss the resources they provide.

There is a need for a study of offender risk perception and hazard awareness. Most offenders are young, African American males, a group shown to have reduced risk perception concerning hazards. It is unclear if offenders are aware of their legal responsibilities ahead of a disaster or whether those responsibilities would influence an evacuation decision. Regarding previously incarcerated offenders, prisons and jails are

often located in rural areas, far from the coast. Its possible offenders may experience risk attenuation while incarcerated. Future research will survey probationers and parolees to gain the offenders' perspective regarding hazardous events.

APPENDIX A – Residential Zoning Codes

Table A1. *Residential Zoning Codes by Zoning District*

Area	Ordinance Year	Residential Zoning Codes
Hancock County	2017	A1, R-1, R-1A, R-2, R-2A, R-3
Waveland	2010	R-1, R-2,R-3,CO-1,CO-2,M1
Bay St Louis	2010	R1, R-1A, R-2, R-3,R-4
Harrison County	2016	A-1, R-1, R-2,R-3
Pass Christian	2013	SmartCode: T2, T3E, T3R, T4+, T4L, T5C, T5H
Long Beach	2013	R-1, R-2, R-3,R-4,R-0
Gulfport	2015	A-1, R-E, R-UE, R-1-15,R-1-10, R-1-7.5,R-1-5, R-2, R-3, R-4, R-O, R-BSmartCode:T3,T4L, T4+,
Biloxi	2018	A, AR, RE, RER, RS-5 SF, RS-7.5 SF RS-10 SF, RM-10, RM-20, RM – 30, RMH
D’Iberville	2015	AG, RE, R-1, R-2, R-3,R-4, R-4A,R-5,R-0

Table A1 (continued).

Jackson County	2017	A-1, A-2, A-3, R-1, R-1A, R-1B, R-2, R-3, R-4, R-5
Gautier	2016	A-1, R-E, R-1, R-2 R-3
Ocean Springs	2016	R-1, R-1A, R-2, R-3, R-4, R-5
Moss Point	2017	A-1, R-1A, R-1B, R-1C, R-2, R-3, R-4
Pascagoula	2017	MR3, SFR6, SFR8, SFR10

Zoning codes were taken from local zoning ordinances and include all districts (residential, mixed-use, and agricultural) that allow for residential property.

APPENDIX B – Python Code for Principal Components Analysis

```
import numpy as np
import math
import numpy.linalg as la
from numpy import genfromtxt

#Data to Numpy array
SDarray = genfromtxt("filepath", delimiter=',', skip_header=0)
print SDarray

#Covariance Matrix
CovMat = np.cov(SDarray)
print(CovMat)

#Correlation Matrix
CorMat = np.corrcoef(SDarray)
print(CorMat)

featvars = []
for r in SDarray:
    featvars.append(np.var(r))

#Eigenvalues and Eigenvectors of Covariance Matrix
evals,evects = la.eig(CovMat)

print('Eigenvectors \n%s' %evects)
#print('\nEigenvalues \n%s' %evals)

# Make a list of (eigenvalue, eigenvector) tuples
eig_pairs = [(np.abs(evals[i]), evects[:,i]) for i in range(len(evals))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eig_pairs.sort(key=lambda x: x[0], reverse=True)

# Visually confirm that the list is correctly sorted by decreasing eigenvalues
print('Eigenvalues in descending order:')
x = 0
ev = []
for i in eig_pairs:
    print(i[0])
    ev.append(i[0])

#Explained Variance

tot = sum(evals)
var_exp = [(i / tot)*100 for i in sorted(evals, reverse=True)]
cum_var_exp = np.cumsum(var_exp)

print "Cumulative Explained Variance" print cum_var_exp

#Factor Loadings between each variable and each principle component
x = 0
for vec in evects:
    #print (vec * math.sqrt(evals[x])) / np.sqrt(featvars)
    factorl = (vec * np.sqrt(ev)) / math.sqrt(featvars[x])
    ## print "Factor Loadings"
    ## print x, factorl[:4] #(vec[:1]) #print by component
    ## print "Eigenvectors"
    ## print x, (vec[:4])
    print x, (vec[:1]),factorl[:1]
    #print np.sqrt(ev)
    x = x+ 1
```

APPENDIX C – Python Code to Collect Offender Support Services from the Mississippi Reentry Guide

```
import urllib2
import urllib #for getaddress location
import math
import re
import csv
cats = ['Criminal Justice', 'Clothing', 'Domestic Abuse', 'Employment', 'Financial/Banking Services',
        'Food', 'Health', 'Mental Health', 'Public Libraries', 'Disability Services', 'Education',
        'Employment', 'AIDS/HIV support', 'Legal', 'Shelter', 'Substance Abuse', 'Veterans']

#URL and Filename will be different for each county.
url = "http://www.msreentryguide.com/resources/county/jackson-county"
filename = r"filepath"
csvfilename = r"filepath"
#code from stack overflow cleans html inside <>
def cleanhtml(raw_html):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, '', raw_html)
    return cleantext

#Function Gets Addresses from Page Source
def GetAddressReentry (url):
    res = urllib2.urlopen(url)
    line = res.readline() #discard the first line
    counter = 100000
    cline = [] #will be cleaned lines in a list
    while line:
        if "<h1>" in line:
            for cat in cats:
                if cat in line:
                    currentcat = cat
        if "<h2>" in line:
            cservice = cleanhtml(line).strip()
            counter = 0
            cline.extend([currentcat, cservice])
            counter = counter + 1
        if ((counter == 2) or (counter == 3)):
            cline.append(cleanhtml(line).strip())
            if (counter == 3):
                print cline
        line = res.readline()
    return cline #returns a list for address locator

#Write Address Info to a text file
def WriteToFile(url, filename):
    AddressList = GetAddressReentry(url) #returns a list
    f = open(filename, "w+")
    for entry in AddressList: #Gets address info from reentry guide
        if entry in cats: #checks for category within address info
            f.write("\n" + str(entry) + ", ") #writes a carriage return before each category
        else:
            f.write(str(entry) + ", ") #will delimit on comma in excel

    f.close()
    #convert text file to CSV
    textfile = csv.reader(open(filename, "r"), delimiter = ',') #columns at commas
    newcsv = csv.writer(open(csvfilename, 'w+'))
    newcsv.writerows(textfile)
    WriteToFile(url, filename)
```

APPENDIX D – Python Code to Project Point Shapefile and Reclassify Offender

Support Services

```
import arcpy
arcpy.env.workspace = r"workspace_path"
PCS = "coordsys_path"
arcpy.env.overwriteOutput = True

#Set Local Variables for Input Shapefiles
InData = "in_filepath"

#Set Local Variables for Output Shapefiles
OutData = "out_filepath"

#Output Coordinate System
Project = arcpy.Describe(PCS).spatialReference

#Project shapefiles to UTM 16
arcpy.Project_management(InData, OutData, Project)

#Add a new field condense categories

def NewCategory (PointShp):
    fields = ["Category", "NewCat"]
    NewField = "NewCat"
    FieldType = "TEXT"
    cursor = arcpy.da.UpdateCursor(PointShp, fields)
    arcpy.AddField_management(PointShp, NewField, FieldType)
    for row in cursor:
        if row[0] == "Mental Health":
            row[1] = "Health"
        elif row[0] == "Substance Abuse":
            row[1] = "Health"
        elif row[0] == "Disability Services":
            row[1] = "Health"
        elif row[0] == "AIDS/HIV support":
            row[1] = "Health"
        else:
            row[1] = row[0]
        cursor.updateRow(row)

NewCategory (OutData)
```


APPENDIX E – IRB Approval Letter



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NOTICE OF COMMITTEE ACTION

The project has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services (45 CFR Part 46), and university guidelines to ensure adherence to the following criteria:

- The risks to subjects are minimized.
- The risks to subjects are reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered regarding risks to subjects must be reported immediately, but not later than 10 days following the event. This should be reported to the IRB Office via the "Adverse Effect Report Form".
- If approved, the maximum period of approval is limited to twelve months.
Projects that exceed this period must submit an application for renewal or continuation.

PROTOCOL NUMBER: 18060404
PROJECT TITLE: A Spatial Examination of Offender Vulnerability and the Impacts to Community Corrections Operations in Coastal Mississippi
PROJECT TYPE: Master's Thesis
RESEARCHER(S): Ashleigh Price
COLLEGE/DIVISION: College of Science and Technology
DEPARTMENT: Geography and Geology
FUNDING AGENCY/SPONSOR: N/A
IRB COMMITTEE ACTION: Expedited Review Approval
PERIOD OF APPROVAL: 06/14/2018 to 06/13/2019
Edward L. Goshorn, Ph.D.
Institutional Review Board

REFERENCES

- Adeola, F. O., and J. S. Picou. 2012. Society for Human Ecology Race, Social Capital, and the Health Impacts of Katrina: Evidence from the Louisiana and Mississippi Gulf Coast. *Human Ecology Review* 19 (1):10–24.
- Adeola, F. O., and J. S. Picou. 2014. Social capital and the mental health impacts of Hurricane Katrina: assessing long-term patterns of psychosocial distress. *International Journal of Mass Emergencies and Disasters* 32 (1):121–156.
- AGS and ESRI. 2018. CrimeRisk Methodology
http://downloads.esri.com/esri_content_doc/dbl/us/AGS_CrimeRisk_Methodology_2017.pdf (last accessed 21 February 2018).
- Anderson, E. 1999. *Code of the Street Decency, Violence, and the Moral Life of the Inner City*. New York, NY: W.W. Norton & Company, Inc.
- Anderson, J. M., J. M. Macdonald, R. Bluthenthal, and S. J. Ashwood. 2013. Reducing Crime by Shaping the Built Environment with Zoning: An Empirical Study of Los Angeles. *University of Pennsylvania Law Review* 161 (3):699–756.
- Arum, R., and G. Lafree. 2008. Educational Attainment, Teacher–Student Ratios, and the Risk of Adult Incarceration Among U.S. Birth Cohorts Since 1910. *Sociology of Education* 81:397–421.
- ASFPM. 2009. HAZUS-MH Flood Model Validation Final Report. Association of State Floodplain Managers, Madison, WI.
- Baumer, E., J. Horney, R. Felson, and J. L. Lauritsen. 2003. Neighborhood Disadvantage and the Nature of Violence. *Criminology* 41 (1):39–71.

- Bernasco, W. 2010. A Sentimental Journey to Crime: Effects of Residential History on Crime Location Choice. *Criminology* 48 (2):389–416.
- Bernasco, W., and R. Block. 2009. Where Offenders Choose to Attack: A Discrete Choice Model of Robberies in Chicago. *Criminology* 47 (1):93–130.
- . 2011. Robberies in Chicago: A Block-Level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points. *Journal of Research in Crime and Delinquency* 48 (1):33–57.
- Blau, J. R., and P. M. Blau. 1982. The Cost of Inequality: Metropolitan Structure and Violent Crime. *American Sociological Review* 47 (1):114–129.
- Boessen, A., and J. R. Hipp. 2018. Parks as crime inhibitors or generators: Examining parks and the role of their nearby context. *Social Science Research* 76:186–201.
- Bolin, B., S. Grineski, and T. Collins. 2005. The geography of despair: Environmental racism the making of South Phoenix, Arizona, USA. *Human Ecology Review* 12 (2):156–168.
- Borden, K. A., M. C. Schmidlein, W. W. Piegorsch, S. L. Cutter, and C. T. Emrich. 2007. Vulnerability of U.S. Cities to Environmental Hazards. *Journal of Homeland Security and Emergency Management* 4 (2):1–23.
- Bouffard, L. A., and L. R. Muftic. 2006. The “Rural Mystique”: Social Disorganization and Violence beyond Urban Communities. *Western Criminology Review* 7 (3):56–66.

- Brantingham, P. L., and P. J. Brantingham. 2010a. Environment, Routine, and Situation Toward a Pattern Theory of Crime. In *Classics in Environmental Criminology*, eds. M. A. Andresen, P. J. Brantingham, and B. J. Kinney, 365–391. Boca Raton, FL: CRC Press.
- . 2010b. Notes on the Geography of Crime (1981). In *Classics in Environmental Criminology*, eds. M. A. Andresen, P. J. Brantingham, and B. J. Kinney, 231–255. Boca Raton, FL: CRC Press.
- Browning, C. R., R. A. Byron, C. A. Calder, L. J. Krivo, M.-P. Kwan, J.-Y. Lee, and R. D. Peterson. 2010. Commercial Density, Residential Concentration, and Crime: Land Use Patterns and Violence in Neighborhood Context. *Journal of Research in Crime and Delinquency* 47 (3):329–357.
- Brusentsev, V., and W. Vroman. 2017. Hurricanes. In *Disasters in the United States: Frequency, Costs, and Compensation*, 77–96. Kalamazoo, Michigan: W.E Upjohn Institute for Employment Research.
- Bureau of Labor Statistics. 2015. Labor force characteristics (CPS). <http://www.bls.gov/cps/lfcharacteristics.htm> (last accessed 19 August 2018).
- Burton, C. G. 2010. Social Vulnerability and Hurricane Impact Modeling. *Natural Hazards Review* 11 (2):58–68.
- Carson, E. A. 2018. Prisoners in 2016. NCJ 251149, Bureau of Justice Statistics, Washington, D.C.
- Carter-Pokras, O., R. E. Zambrana, S. E. Mora, and K. A. Aaby. 2007. Emergency Preparedness: Knowledge and Perceptions of Latin American Immigrants. *Journal of Health Care for the Poor and Underserved* 18 (2):465–481.

- Chakraborty, J. 2009. Automobiles, Air Toxics, and Adverse Health Risks: Environmental Inequities in Tampa Bay, Florida. *Annals of the Association of American Geographers* 99 (4):674–697.
- Chakraborty, J., G. A. Tobin, and B. E. Montz. 2005. Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards. *Natural Hazards Review* 6 (1):23–33.
- City of Gulfport. 2015. Appendix A - Zoning, Sec. III District Regulations. Gulfport, Mississippi Code of Ordinances. https://library.municode.com/ms/gulfport/codes/code_of_ordinances (last accessed 15 June 2018).
- City of Pass Christian. 2013. Pass Christian Smart Code Ordinance. [https://pass-christian.com/PDF/Smartcode 10.2013.pdf](https://pass-christian.com/PDF/Smartcode%2010.2013.pdf) (last accessed 22 June 2018).
- Clarke, R. V., and M. Felson. 2008. *Routine Activity and Rational Choice*. New York, New York: Routledge.
- Clear, T. R. 2007. *Imprisoning Communities: How Mass Incarceration Makes Disadvantaged Neighborhoods Worse*. New York, New York: Oxford University Press.
- Cochran, D. M., and B. Kar. 2016. Wireless Emergency Alerts: Final Report: An Integrated Approach to Geo-Target At-Risk Communities and Deploy Effective Crisis Communication Approaches. Department of Homeland Security, Washington, DC.

- Cochran, J. C., D. P. Mears, and W. D. Bales. 2017. Who Gets Visited in Prison? Individual-and Community-Level Disparities in Inmate Visitation Experiences. *Crime & Delinquency* 63 (5):545–568.
- Cochran, J. C., D. P. Mears, W. D. Bales, and E. A. Stewart. 2016. Spatial Distance, Community Disadvantage, and Racial and Ethnic Variation in Prison Inmate Access to Social Ties. *Journal of Research in Crime and Delinquency* 53 (2):220–254.
- Cohen, L. E., and M. Felson. 1979. Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review* 44 (4):588.
- Cole, J. M., and B. L. Murphy. 2014. Rural hazard risk communication and public education: Strategic and tactical best practices. *International Journal of Disaster Risk Reduction* 10:292–304.
- Collins, T. W., S. Grineski, J. Chakraborty, M. C. Montgomery, and M. Hernandez. 2015. Downscaling Environmental Justice Analysis: Determinants of Household-Level Hazardous Air Pollutant Exposure in Greater Houston. *Annals of the Association of American Geographers* 105 (4):684–703.
- CSG Justice Center. 2019. National Inventory of the Collateral Consequences of Conviction. https://niccc.csgjusticecenter.org/database/results/?jurisdiction=215&consequence_category=&narrow_category=&triggering_offense_category=&consequence_type=&duration_category=&page_number=1 (last accessed 9 January 2019).
- Cutter, S. L., B. J. Boruff, and W. L. Shirley. 2003. Social Vulnerability to Environmental Hazards. *Social Science Quarterly* 84 (2):242–261.

- Cutter, S. L., J. T. Mitchell, and M. S. Scott. 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. *Annals of the Association of American Geographers* 90 (4):713–737.
- Deakin, J., H. Smithson, J. Spencer, and J. Medina-Ariza. 2007. Taxing on the Streets: Understanding the Methods and Process of Street Robbery. *Crime Prevention and Community Safety* 9:52–67.
- Delp, L., L. Podolsky, and T. Aguilar. 2009. Risk Amid Recovery: Occupational Health and Safety of Latino Day Laborers in the Aftermath of the Gulf Coast Hurricanes. *Organization & Environment* 22 (4):479–490.
- Demotto, N., and C. P. Davies. 2006. A GIS Analysis of the Relationship between Criminal Offenses and Parks in Kansas City, Kansas. *Cartography and Geographic Information Science* 33 (2):141–157.
- Denver, M., J. T. Pickett, and S. T. Bushway. 2017. The Language of Stigmatization and the Mark of Violence: Experimental Evidence on the Social Construction and Use of Criminal Record Stigma. *Criminology* 55 (3):664–690.
- DHS. 2006. A Performance Review of FEMA’s Disaster Management Activities in Response to Hurricane Katrina. Department of Homeland Security. Department of Homeland Security, Washington, DC.
- EmpowerMS.org. 2019. Getting a Job is Not that Simple. <http://empowerms.org/getting-a-job-is-not-that-simple/> (last accessed 2 January 2019).
- ESRI. 2018. Introduction to the Hazus Storm Surge Model. <https://www.esri.com/training> (last accessed 8 April 2018).

- Faas, A. J. 2016. Disaster vulnerability in anthropological perspective. *Annals of Anthropological Practice* 40 (1):14–27.
- FEMA. 2009a. Flood Insurance Study Hancock County, Mississippi and Incorporated Areas Volume 1 of 2. Federal Emergency Management Agency, Washington, DC.
- . 2009b. Flood Insurance Study Hancock County, Mississippi Volume 1 of 2. Federal Emergency Management Agency, Washington, DC.
- . 2009c. Flood Insurance Study Harrison County Mississippi and Incorporated Areas Volume 1 of 3. Federal Emergency Management Agency, Washington, DC.
- . 2009d. Flood Insurance Study Jackson County, Mississippi and Incorporated Areas Volume 1 of 2. Federal Emergency Management Agency, Washington, DC.
- . 2012a. Multi-hazard Loss Estimation Methodology Flood Model Hazus-MH Technical Manual. Federal Emergency Management Agency, Washington, DC.
- . 2012b. Multi-hazard Loss Estimation Methodology Hurricane Model Hazus-MH 2.1 Technical Manual. Federal Emergency Management Agency, Washington, DC.
- . 2017a. Flood Insurance Study Harrison County, Mississippi Volume 1. Federal Emergency Management Agency, Washington, DC.
- . 2017b. Flood Insurance Study Jackson County, Mississippi Volume 1. Federal Emergency Management Agency, Washington, DC.
- . 2018. Hazus Hurricane Model User Guidance. Federal Emergency Management Agency, Washington, DC.
- FFFM. 2018. Families First for Mississippi Classes By Counties.
<https://www.familiesfirstforms.org/baystlouis> (last accessed 12 December 2018).

- FMS. 2015. Mississippi Reentry Guide. <http://www.msreentryguide.com/county-resources> (last accessed 3 December 2017).
- Gares, C. E., and B. E. Montz. 2014. Disaster Vulnerability of Migrant and Seasonal Farmworkers: A Comparison of Texas and North Carolina. *Southeastern Geographer* 54 (1):36–54.
- Grineski, S., T. W. Collins, P. Ford, R. Fitzgerald, R. Aldouri, G. Velazquez-Angulo, M. de Lourdes Romo Aguilar, and D. Lu. 2012. Climate change and environmental injustice in a bi-national context. *Applied Geography* 33:25–35.
- Groen, J. A., M. J. Kutzbach, and A. E. Polivka. 2017. Storms and Jobs: The Effect of Hurricanes on Individuals' Employment and Earnings over the Long Term. Working Paper 499, Bureau of Labor Statistics. Washington, DC.
- Groff, E. R., and B. Lockwood. 2014. Criminogenic Facilities and Crime across Street Segments in Philadelphia: Uncovering Evidence about the Spatial Extent of Facility Influence. *Journal of Research in Crime and Delinquency* 51 (3):277–314.
- Groff, E. R., and T. McEwen. 2006. *Exploring the Spatial Configuration of Places Related to Homicide Events*. Institute for Law and Justice. Alexandria, VA.
- Haddow, G., J. Bullock, and D. Coppola. 2014. *Introduction to Emergency Management* Fifth. eds. P. Chester and A. Hodge. Waltham, MA: Butterworth-Heinemann.
- Hairston, J. C. F. 2002. Prisoners and Families: Parenting Issues During Incarceration. Paper presented at the From Prison to Home Conference, Bethesda, MD January 30-31. Bethesda, MD.

- Harding, D. J., J. D. Morenoff, and C. W. Herbert. 2013. Home Is Hard to Find: Neighborhoods, Institutions, and the Residential Trajectories of Returning Prisoners. *The Annals of the American Academy of Political and Social Science* 647:214–236.
- Harlow, C. W. 2003. Education and Correctional Populations. NCJ 195670, Bureau of Justice Statistics. Washington, D.C.
- Harrison County, M. 2018. Property Search Application. Harrison County Online Zone Mapping. <http://harrisonms.geopowered.com/propertysearch/> (last accessed 19 June 2018).
- Hattery, A., and E. Smith. 2010. *Prisoner Reentry and Social Capital The Long Road to Reintegration*. Lanham, MD: Lexington Books.
- HCLS. 2019a. Hancock County Library System. <http://www.hancocklibraries.info/> (last accessed 20 January 2019).
- . 2019b. Harrison County Library System. <https://harrison.lib.ms.us/> (last accessed 20 January 2019).
- Hill, J. B., and J. Banks. 2018. Bitches, Fishes, and Monsters: Prison Slang and Nonhuman Animal Terminology. *Society & Animals* Forthcoming.
- Hipp, J. R. 2007. Income Inequality, Race, and Place: Does the Distribution of Race and Class within Neighborhoods affect Crime Rates? *Criminology* 45 (3):665–697.
- . 2010. What is the “Neighbourhood” in Neighbourhood Satisfaction? Comparing the Effects of Structural Characteristics Measured at the Micro-neighbourhood and Tract Levels. *Urban Studies* 47 (12):2517–2536.

- Hipp, J. R., J. Jannetta, R. Shah, and S. Turner. 2011. Parolees' Physical Closeness to Social Services: A Study of California Parolees. *Crime & Delinquency* 57 (1):102–129.
- Hipp, J. R., and C. E. Kubrin. 2016. Do Fringe Banks Create Fringe Neighborhoods? Examining the Spatial Relationship between Fringe Banking and Neighborhood Crime Rates. *Justice Quarterly* 33 (5):755–784.
- Hipp, J. R., J. Petersilia, and S. Turner. 2010. Parolee Recidivism in California: The Effect of Neighborhood Context and Social Service Agency Characteristics. *Criminology* 48 (4):947–979.
- Howell, J. C. 1998. Youth Gangs: An Overview. U.S. Department of Justice Office of Justice Programs, Washington, DC.
- Hughes, T. A., D. J. Wilson, and A. J. Beck. 2001. Trends in State Parole, 1990-2000. NCJ 184735, Bureau of Justice Statistics. Washington, D.C.
- Jackson County. 2018. Jackson County Tax Parcel Viewer. Jackson County GIS and Web Mapping. <https://webmap.co.jackson.ms.us/> (last accessed 22 June 2018).
- JGRLS. 2019. Jackson George Regional Library System. <http://www.jgrls.org/> (last accessed 20 January 2019).
- Jensen, J. R. 2005. Image Enhancement. In *Introductory Digital Image Processing*, ed. K. C. Clarke, 255–335. Upper Saddle River, NJ: Pearson Prentice Hall.
- Kaible, D. 2018. Probation and Parole in the United States, 2016. NCJ 251148, Bureau of Justice Statistics. Washington, D.C.

- Kent, J., M. Leitner, and A. Curtis. 2006. Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions. *Computers, Environment and Urban Systems* 30 (2):181–200.
- Kirk, D. S. 2009. A Natural Experiment on Residential Change and Recidivism: Lessons from Hurricane Katrina. *American Sociological Review* 74 (3):484–505.
- . 2012. Residential Change As A Turning Point In The Life Course Of Crime: Desistance Or Temporary Cessation? *Criminology* 50 (2):329–358.
- Krivo, L. J., and R. D. Peterson. 1996. Extremely Disadvantaged Neighborhoods and Urban Crime. *Social Forces* 75 (2):619–650.
- Kubrin, C. E., and E. Stewart. 2006. Predicting Who Reoffends: The Neglected Role of Neighborhood Context in Recidivism Studies. *Criminology* 44 (1):165–197.
- Lazarus, N. W. 2016. A County-Level Risk Assessment of the Deep Water Horizon Oil Spill in the Gulf of Mexico. *Geographical Review* 106 (3):360–380.
- Lee, J., B. J. Blackmon, J. Y. Lee, D. M. Cochran, and T. A. Rehner. 2018. An exploration of posttraumatic growth, loneliness, depression, resilience, and social capital among survivors of Hurricane Katrina and the Deepwater Horizon Oil Spill. *Journal of Community Psychology* :1–15.
- Logan, J. R., and Z. Xu. 2015. Vulnerability to hurricane damage on the U.S. Gulf Coast since 1950. *The Geographical Review* 105 (2):133–155.
- Longenecker, G. H. E. 2012. Hazus-MH Coastal Flood Model FEMA Region IV Standard Operating Procedure for Coastal Flood Hazard and Loss Analysis. Federal Emergency Management Agency Atlanta, GA.

- Manyena, S. 2006. The Concept of Resilience Revisited. *Disasters* 30 (4):433–450.
- McDowell, M. G. 2013. “Becoming a waste land where nothing can survive”: resisting state-corporate environmental crime in a “forgotten” place. *Contemporary Justice Review: Issues in Criminal, Social, and Restorative Justice* 16 (4):394–411.
- MDOC. 2013. Final Report Mississippi Corrections and Criminal Justice Task Force. Mississippi Department of Corrections, Jackson, MS.
- . 2014. Frequently asked questions about House Bill 585. Mississippi Department of Corrections, Jackson, MS.
- . 2018. Mississippi Department of Corrections Fact Sheet as of November 1, 2018. Mississippi Department of Corrections, Jackson, MS.
- Mears, D. P., and J. C. Cochran. 2015. *Prisoner Reentry in the Era of Mass Incarceration* eds. J. Westby, K. DeRosa, and L. Weber. Thousand Oaks, CA: Sage Publications, Inc.
- Mennis, J., and P. W. Harris. 2013. Spatial Contagion of Male Juvenile Drug Offending Across Socioeconomically Homogeneous Neighborhoods. In *Crime Modeling and Mapping Using Geospatial Technologies*, ed. M. Leitner, 227–248. New York, NY: Springer Dordrecht Heidelberg.
- Mennis, J., P. W. Harris, Z. Obradovic, A. J. Izenman, H. E. Grunwald, and B. Lockwood. 2011. The Effect of Neighborhood Characteristics and Spatial Spillover on Urban Juvenile Delinquency and Recidivism. *The Professional Geographer* 63 (2):174–192.
- Miller, J., J. M. Caplan, and M. Ostermann. 2016. Assessing the Effects of Local Crime Hotspots on Parole Recidivism. *The Prison Journal* 96 (3):437–461.

- Montz, B. E., G. A. Tobin, and R. R. Hagelman. 2017. *Natural Hazards Explanation and Integration* Second Edi. New York, New York: The Guilford Press.
- MORE. 2019. FAQ's. <https://www.morems.org/faqs/> (last accessed 3 January 2019).
- Morenoff, J. D., R. J. Sampson, and S. W. Raudenbush. 2001. Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence. *Criminology* 39 (3):517–559.
- MSSP. 2018. Mississippi Gulf Coast Resources.
http://www.mssp.uscourts.gov/sites/mssp/files/GULFPORT_COMMUNITY_RESOURCES.pdf (last accessed 4 April 2018).
- Murphy, B. L. 2007. Locating social capital in resilient community-level emergency management. *Natural Hazards* 41:297–315.
- Murray, A. T., T. H. Grubestic, E. A. Mack, R. Wei, S. J. Rey, L. Anselin, and M. L. Griffin. 2013. Convicted Sex Offender Residential Movements. In *Crime Modeling and Mapping Using Geospatial Technologies*, ed. M. Leitner, 51–71. New York, NY: Springer Dordrecht Heidelberg.
- Muthukumar, S. 2005. Riverine Flood Modeling in HAZUS-MH: Overview of the Implementation. Paper presented at the *Georgia Water Resources Conference*, Athens, GA, April 25
- Nieuwebeerta, P., P. L. Mccall, H. Elffers, and K. Wittebrood. 2008. Neighborhood Characteristics and Individual Homicide Risks Effects of Social Cohesion, Confidence in the Police, and Socioeconomic Disadvantage. *Homicide Studies* 12 (1):90–116.

- NOAA. 2005. Preliminary Report Hurricane Katrina Storm Tide Summary. National Oceanic and Atmospheric Administration, Silver Spring, MD.
- . 2008. Gulf of Mexico Summary. National Oceanic and Atmospheric Administration Office of Science and Technology, Silver Spring, MD.
- Oulahen, G., L. Mortsch, K. Tang, D. Harford, and D. Harfordz. 2017. Unequal Vulnerability to Flood Hazards: Ground Truthing a Social Vulnerability Index of Five Municipalities in Metro Vancouver, Canada. *Annals of the Association of American Geographers* 105 (3):473–495.
- Pager, D. 2003. The Mark of a Criminal Record. *American Journal of Sociology* 108 (5):937–975.
- Parker, K. F., and P. L. McCall. 1999. Structural Conditions and Racial Homicide Patterns: A Look at the Multiple Disadvantages in Urban Areas. *Criminology* 37 (3):447–478.
- PEER. 2006. The Impact of Hurricane Katrina on Mississippi’s Commercial Public Ports and Opportunities for Expansion of the Ports. Joint Legislative Committee on Performance Evaluation and Expenditure Review, Jackson, MS.
- Petersilia, J. 2003. *When Prisoners Come Home: Parole and Prisoner Reentry*. New York, New York: Oxford University Press, Inc.
- Peterson, R. D., and L. J. Krivo. 2010. *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide*. New York, New York: Russel Sage Foundation.
- Pettit, B., and B. Western. 2004. Mass Imprisonment and the Life Course: Race and Class Inequality in U.S. Incarceration. *American Sociological Review* 69 (2):151–169.

- Prasad, S. 2012. An Assessment of Human Vulnerability to Hazards in the US Coastal Northeast and Mid-Atlantic. *Southeastern Geographer* 52 (3):282–298.
- Prelog, A. J. 2016. Modeling the Relationship between Natural Disasters and Crime in the United States. *Natural Hazards Review* 17 (1).
- Prelog, A. J., and L. M. Miller. 2013. Perceptions of Disaster Risk and Vulnerability in Rural Texas. *Journal of Rural Social Sciences* 28 (3):1–31.
- Pulido, L. 2015. Geographies of race and ethnicity 1. *Progress in Human Geography* 39 (6):809–817.
- Putnam, R. D. 2000. *Bowling Alone*. New York, New York: Simon & Schuster, Inc.
- Qiu, X., S. Wu, and Y. Chen. 2010. Effects of Threshold Drainage Area and Study Region Size on Hazus Flood Analysis. *Cartography and Geographic Information Science* 37 (2):93–104.
- Ratcliffe, J. H., and E. S. Mccord. 2007. A Micro-Spatial Analysis of the Demographic and Criminogenic Environment of Drug Markets in Philadelphia. *The Australian and New Zealand Journal Of Criminology* 40 (1):43–63.
- Remo, J. W. F., M. Carlson, and N. Pinter. 2012. Hydraulic and flood-loss modeling of levee, floodplain, and river management. *Natural Hazards* 61:551–575.
- Remo, J. W. F., N. Pinter, and M. Mahgoub. 2016. Assessing Illinois’s flood vulnerability using Hazus-MH. *Natural Hazards* 81:265–287.
- Reynald, D., M. Averdijk, H. Elffers, and W. Bernasco. 2008. Do Social Barriers Affect Urban Crime Trips? The Effects of Ethnic and Economic Neighbourhood Compositions on the Flow of Crime in The Hague, The Netherlands. *Built Environment* 34 (1):21–31.

- Robertson, C. 2015. Mississippi's Recovery After Katrina Holds Lessons for Policy Makers. <https://www.nytimes.com/2015/08/29/us/mississippis-recovery-after-hurricane-katrina-holds-lessons-for-policy-makers.html> (last accessed 12 December 2018)
- Rosenkoetter, M. M., E. K. Covan, B. K. Cobb, S. Bunting, and M. Weinrich. 2007. Perceptions of Older Adults Regarding Evacuation in the Event of a Natural Disaster. *Public Health Nursing* 24 (2):160–168.
- Rossmo, K. D. 2000. *Geographic Profiling*. Boca Raton, FL: CRC Press.
- . 2012. Recent Developments in Geographic Profiling. *Policing: A Journal of Policy & Practice* 6 (2):144–150.
- Sampson, R. J., J. D. Morenoff, and T. Gannon-Rowley. 2002. Assessing Neighborhood Effects: Social Processes and New Directions in Research. *Annual Review of Sociology* 28:443–478.
- Sampson, R. J., and S. W. Raudenbush. 2004. Seeing Disorder: Neighborhood Stigma and the Social Construction of “Broken Windows.” *Social Psychology Quarterly* 67 (4):319–342.
- Sayers, P., E. C. Penning-Rowsell, and M. Horritt. 2018. Flood vulnerability, risk, and social disadvantage: current and future patterns in the UK. *Regional Environmental Change* 18:339–352.
- Scawthorn, C., N. Blais, H. Seligson, E. Tate, E. Mifflin, W. Thomas, J. Murphy, and C. Jones. 2006. HAZUS-MH Flood Loss Estimation Methodology. I: Overview and Flood Hazard Characterization. *Natural Hazards Review* 7 (2):60–71.

- Scawthorn, C., P. Flores, N. Blais, H. Seligson, E. Tate, S. Chang, E. Mifflin, W. Thomas, J. Murphy, C. Jones, and M. Lawrence. 2006. HAZUS-MH Flood Loss Estimation Methodology. II. Damage and Loss Assessment. *Natural Hazards Review* 7 (2):72–81.
- Settembrino, M. R. 2017. Exercising Agency: How Men Experiencing Homelessness Employ Human, Social, and Cultural Capital to Mitigate Natural Hazards Risk. *Natural Hazards Review* 18 (4).
- Shultz, S. 2017. Accuracy of HAZUS General Building Stock Data. *Natural Hazards Review* 18 (4):1–10.
- Skogan, W. G. 1992. *Disorder and Decline: Crime and the Spiral of Decay in American Neighborhoods*. Berkeley, CA: University of California Press.
- Small, M. L., and M. McDermott. 2006. The Presence of Organizational Resources in Poor Urban Neighborhoods: An Analysis of Average and Contextual Effects. *Social Forces* 84 (3):1697–1724.
- Sohn, D.-W. 2016. Do all commercial land uses deteriorate neighborhood safety?: Examining the relationship between commercial land-use mix and residential burglary. *Habitat International* 55:148–158.
- Stahler, G. J., J. Mennis, S. Belenko, W. N. Welsh, M. L. Hiller, and G. Zajac. 2013. Predicting Recidivism for Released State Prison Offenders Examining the Influence of Individual and Neighborhood Characteristics and Spatial Contagion on the Likelihood of Re-incarceration. *Criminal Justice and Behavior* 40 (6):690–711.

- Stitt, B. G., M. Nichols, and D. Giacomassi. 2003. Does the Presence of Casinos Increase Crime? An Examination of Casino and Control Communities. *Crime & Delinquency* 49 (2):253–284.
- Stucky, T. D., and J. R. Ottensmann. 2009. Land Use and Violent Crime. *Criminology* 47 (4):1223–1264.
- The Sentencing Project. 2013. A Lifetime of Punishment: The Impact of the Felony Drug Ban on Welfare Benefits. <https://www.sentencingproject.org/publications/a-lifetime-of-punishment-the-impact-of-the-felony-drug-ban-on-welfare-benefits/>. (accessed 3 March 2018).
- Tita, G., J. Cohen, and J. Engberg. 2005. An Ecological Study of the Location of Gang “Set Space.” *Social Problems* 52 (2):272–299.
- Tsuchiya, N., N. Nakaya, T. Nakamura, A. Narita, M. Kogure, J. Aida, I. Tsuji, A. Hozawa, and H. Tomita. 2017. Impact of social capital on psychological distress and interaction with house destruction and displacement after the Great East Japan Earthquake of 2011. *Psychiatry and Clinical Neurosciences* 71:52–60.
- Ueland, J., and B. Warf. 2006. Racialized Topographies: Altitude and Race in Southern Cities. *Geographical Review* 96 (1):50–78.
- UNISDR. 2017. Terminology. <https://www.unisdr.org/we/inform/terminology#letter-c> (last accessed 10 February 2017).
- Vigdor, J. 2008. The Economic Aftermath of Hurricane Katrina. *Journal of Economic Perspectives* 22 (4):135–154.
- Vogel, M., and S. J. South. 2016. Spatial Dimensions of the Effect of Neighborhood Disadvantage on Delinquency. *Criminology* 54 (3):434–458.

- Walker, G., and K. Burningham. 2011. Flood risk, vulnerability and environmental justice: Evidence and evaluation of inequality in a UK context. *Critical Social Policy* 31 (2):216–240.
- Wallace, D. 2015. Do Neighborhood Organizational Resources Impact Recidivism? *Sociological Inquiry* 85 (2):285–308.
- Wallace, Z. C., L. Keys-Mathews, and A. A. Hill. 2015. The role of experience in defining tornado risk perceptions: A case from the 27 April 2011 outbreak in rural Alabama. *Southeastern Geographer* 55 (4).
- Wang, F., and M. T. Arnold. 2008. Localized income inequality, concentrated disadvantage and homicide. *Applied Geography* 28:259–270.
- Wang, F., and W. W. Minor. 2002. Where the Jobs Are: Employment Access and Crime Patterns in Cleveland. *Annals of the Association of American Geographers* 92 (3):435–450.
- Warr, M. 1998. Life-Course Transitions and Desistance from Crime. *Criminology* 36 (2):183–216.
- Wehrman, M. M. 2010. Race, concentrated disadvantage, and recidivism: A test of interaction effects. *Journal of Criminal Justice* 38:538–544.
- Wickes, R., C. Britt, and L. Broidy. 2017. The resilience of neighborhood social processes: A case study of the 2011 Brisbane flood. *Social Science Research* 62:96–119.
- Wilcox, P., N. Quisenberry, D. T. Cabrera, and S. Jones. 2004. Busy places and broken windows? Toward defining the role of physical structure and process in community crime models. *The Sociological Quarterly* 45 (2):185–207.

- van Wilsem, J. 2009. Urban Streets as Micro Contexts to Commit Violence. In *Putting Crime in its Place Units of Analysis in Geographic Criminology*, eds. D. Weisburd, W. Bernasco, and G. J. N. Bruinsma, 199–216. New York, NY: Springer Science.
- Wood, M. M., D. S. Mileti, M. Kano, M. M. Kelley, R. Regan, and L. B. Bourque. 2012. Communicating Actionable Risk for Terrorism and Other Hazards. *Risk Analysis* 32 (4):601–615.
- Wood, N. J., C. G. Burton, and S. L. Cutter. 2010. Community variations in social vulnerability to Cascadia-related tsunamis in the U.S. Pacific Northwest. *Natural Hazards* 52 (2):369–389.
- Wood, V. T., and R. A. Weisman. 2003. A Hole in the Weather Warning System. *Bulletin of the American Meteorological Society* 84 (2):194–194.
- Wright, R. T., and S. H. Decker. 1997. *Armed Robbers in Action: Stickups and Street Culture*. Boston, MA: Northeastern University Press.
- Wu, S.-Y., B. Yarnal, and A. Fisher. 2002. Vulnerability of coastal communities to sealevel rise: a case study of Cape May county, New Jersey, USA. *Climate Research* 22 (3):255–270.
- Yoon, D. K. 2012. Assessment of social vulnerability to natural disasters: a comparative study. *Natural Hazards* 63:823–843.
- Zeng, Z. 2018. Jail Inmates in 2016. NCJ 215210, Bureau of Justice Statistics. Washington, D.C.

Zhang, W. 2016. Does compact land use trigger a rise in crime and a fall in ridership? A role for crime in the land use-travel connection. *Urban Studies* 53 (14):3007–3026