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# Flooding and Industrial Swine Farming in North Carolina: Implications of Natech Hazards on the Assessment of Environmental Justice

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by

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## Abstract

"Natech" events, in which natural hazards trigger anthropogenic hazards, are becoming increasingly common. Methodologies for measuring the impact of natech events on environmental justice assessments are lacking, particularly in rural scenarios. This study used additive, multiplicative, and z-score threshold methods of combining the density of industrial swine farms in eastern North Carolina and the presence of flood risk to determine whether or not natech risk exhibits emergent socioeconomic indicators and whether areas of high natech constitute environmental injustice. The multiplicative and z-score threshold methods generated variables representing natech risk to compare to socioeconomic indicators, as well as statistically significant hotspots. Measuring the correlation of those two variables, swine density, and flood risk to socioeconomic variables served as a means to assess whether emergent social indicators existed only when constituent hazards overlapped. The hotspots and the additive bivariate map provided three sample areas used to measure difference in socioeconomic variables from the rest of the study area. The highest natech risk in all three methods was found in the Cape Fear and Neuse River Basins. The lack of unique correlations between the natech variables and socioeconomic variables did not indicate emergent socioeconomic indicators associated with natech risk. The sample areas exhibited significantly lower incomes and higher rates of Hispanic and disabled residents, indicating environmentally unjust impacts.

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# Chapter 1: Introduction

Disasters often draw public attention to socioeconomic power systems like racism and class division (Ermus, 2018). Researchers and policy experts have long noted that adverse impacts of environmental hazards are often more frequent or severe for racially or economically marginalized communities (US Inst. of Med., 1999). In the United States, this trend had become mainstream knowledge due in large part to publicity of uneven impacts from several major hurricanes of the past two decades (Picou, 2009; Madrigano et al., 2018; García-Lopez, 2018). As such, the bodies of scholarship on environmental justice and disaster research have grown together substantially in the past two decades and are likely to continue doing so (Gill & Ritchie, 2018).

Experts predict that future disasters are likely to pose more severe implications for environmental justice for three main reasons. First, climate change is likely to exacerbate the frequency and magnitude of certain natural hazards, such as hurricanes, thereby increasing risk of disasters overall (Mohai, Pellow, & Roberts, 2009; Jurjonas & Seekamp, 2018). Second, the increasing urbanization and densification of human populations creates greater vulnerability by concentrating both at-risk communities and systems of critical infrastructures into smaller and smaller areas (Quarantelli, 1996). Lastly, global consumerism has incentivized the industrialized production of goods, which in turn increases the outputs of hazardous by-products and waste materials, as well as the amount of facilities necessary for storing, transporting, and treating those hazardous materials (Ermus, 2018; Girgin, Necci, & Krausmann, 2019). These trends are anticipated to result in future disasters that are not only more common and severe, but that also carry a greater likelihood of triggering cascades of secondary and tertiary hazards from anthropogenic sources, such as when floods cause the release of hazardous materials from chemical manufacturers (Gill & Ritchie, 2018).

Scholars have coined the term “natech hazards” to refer to scenarios in which natural hazards trigger a secondary, technological hazard (Showalter & Myers, 1994). Though there remains some ambiguity as to what kinds of events should be considered “natech hazards” (Nascimento & Alencar, 2016), the scientific consensus is that such events have been increasing (Showalter & Myers, 1994; Young, Balluz, & Malilay, 2004; Gill & Ritchie, 2018) and will continue to increase in the future as long as the densification of industrial development in hazard-prone areas continues (Cruz & Suarez-Paba, 2019; Girgin, Necci, & Krausmann, 2019). Better understanding the spatial and demographic distribution of vulnerability to the concurrent or secondary hazards associated with natech events has been of recent interest to the environmental justice community for purposes such as public health monitoring (Horney et al., 2018), urban planning (Zhang, 2010), and environmental law (Weeden, 2006).

In the United States, the discourse on the intersection of environmental justice and natech events is fairly young and has two significant research gaps. First, the existing research has predominantly focused its attention on urban case studies (Picou, 2009; Slack et al., 2020). An emphasis on urban areas is understandable because the concentration of vulnerable populations and critical infrastructures makes growing natech risk particularly concerning for urban decision makers. On the other hand, while a lower density of development may reasonably be expected to result in fewer natech scenarios *generally*, it should not be assumed that rurality universally lends itself to lesser natech vulnerability. Second, much existing research has largely focused on a few specific industrial sectors, such as petroleum, chemical manufacturing, or radiological materials (Cruz & Krausmann, 2008; Madrigano et al., 2018). Other sectors, such as large-scale agriculture, have yet to receive the same level of attention. Rural and agricultural communities have their own unique vulnerabilities, such as comparatively little political representation and smaller tax bases from which to fund mitigation efforts (Jurjonas & Seekamp, 2018). To better understand the disaster management implications of rural facilities and the industrialization of agriculture, a better understanding of natech vulnerability in rural contexts is needed.

A recent intersection of environmental justice and natech risk in a rural context has been the vulnerability of coastal North Carolina's swine-farming industry to hurricanes and flooding. Concentrated animal feeding operations (CAFOs) for swine typically construct vast open-air "lagoons" for storing and anaerobically treating large volumes of waste (Chastain, Camberato, Albrecht, & Adams, 2003). North Carolina's coastal plain is characterized by a high density of large swine CAFOs, with a large number of these experiencing high-volume releases of concentrated waste in the past three decades. During Hurricanes Floyd in 1999, Matthew in 2016, and Florence in 2018 (Schmidt, 2000; Pierre-Louis, 2018), flooding and heavy precipitation resulted in the overtopping of these ponds or the erosion of the earthen berms that contain them. Many previous case studies of North Carolina's swine industry by public health and environmental justice scholars have generally agreed that proximity-based exposure to swine CAFOs in the region disproportionately affects Black and low-income communities (e.g., Wing, Cole, & Grant, 2000; Mirabelli, Wing, Marshall, & Wilcosky, 2006; Nicole, 2013). In spite of the historical salience of such flood-triggered waste releases in the region, only one prior study has addressed this issue locally (Wing, Freedman, and Band, 2002), and that study focused solely on whether communities affected by Hurricane Floyd were predominantly Black or White. There has not yet been much inquiry into how or whether the overlap of flood risk shapes the assessment of environmental injustice.

This study aimed to map the potential for waste release natechs on the North Carolina coastal plain and better understand how assessments of environmental injustice around local CAFOs might change when flood risk is also considered. To broach this issue, the distribution of both CAFOs and flood risk had to be mapped together to determine where a waste release is most plausible. Once this information was gathered, this research sought to address two key research questions about how natech risks affect environmental justice. First, are there emergent socioeconomic indicators of natech risk that do not appear without both constituent hazards present? Second, how does the socioeconomic status of areas where CAFOs and flood risk co-occur vary from those where only one constituent risk predominates? Developing a more nuanced understanding of the patterns exhibited by socioeconomic indicator variables change with the addition of multiple co-present hazards is a first step towards developing better methodologies for better environmental justice assessments in the face of natech risks that are becoming increasingly frequent and complex.

# Chapter 2: Background and Context

## *2.1: Origins of the "Natech" Hazards Concept*

Though the term "natech" was not itself coined until the mid-1990s (Showalter & Myers, 1994), Gill and Ritchie (2018) attribute the origins of the concept to the global industrial boom that followed World War II. The prevailing paradigm before the World Wars was that disasters were 'acts of God' (Furedi, 2007, p. 483), and definitions of the word "disaster" did not expand to include anthropogenic causes until the 1960s and 70s (Quarantelli, 1981). It was not until post-war economic growth in these decades contributed to widespread industrialization and mass media that technological disasters like Love Canal or Three Mile Island gained widespread public visibility (Gill & Ritchie, 2017). Since then, etiological discourse on disasters has expanded to include technological and, more broadly, anthropogenic sources (Quarantelli, 2001). After this broadening phase, it became clear that an increasing number of events could not be easily categorized as being exclusively 'natural' or 'technological,' hence the portmanteau 'natech.' Gill and Ritchie (2018) consider the 1972 Buffalo Creek dam failure to be a watershed moment in the rise of natech research, as it provided a clear and well-publicized example of a technological system whose failure was attributable to a natural trigger, specifically heavy precipitation (pp. 42-43). By the 1990s, it became accepted knowledge in disaster research that events like these were becoming increasingly common (Showalter & Myers, 1994; Quarantelli, 1996).

Natech research has had significant growth since the 1990s, but still has several shortcomings. First, the advancement of natech studies to date has predominantly been driven by European scholarship, and while the 2011 Tōhoku tsunami and following Fukushima Daiichi nuclear disaster have spurred a rapidly growing body of research in East Asia, the natech concept has not yet achieved the same level of popularity in the United States (Nascimento & Alencar, 2016). Second, a lack of consistency in the categorization of hazards has meant that documentation of natech disasters has been lacking. Natech events, particularly hazardous releases, are likely far more common that current databases would suggest (WHO, 2018). Girgin, Necci, and Krausmann (2019) list the lack of consistent terminology, the lack of existing knowledge on the vulnerability of equipment in many industries, and the breadth of technologies susceptible to environmental hazards as some of the obstacles to the development of natech methodologies. The critical role of individual, private-sector facilities has also been identified as a frequent obstacle to research, as key information about risk factors like equipment, stored chemicals, or safety protocols is often site-specific and/or proprietary (Young et al., 2004). Many studies have focused on specific kinds of industrial equipment or specific sectors by necessity because of the sheer variety of possible scenarios that might be considered 'natech.' Third, a review of natech literature by Cruz and Suarez-Paba (2019) found that existing natech studies have overwhelmingly focused on risk assessment, but not the perception, communication, or reduction of natech risk. Risk reduction recommendations that have arisen from the research have primarily consisted of better on-site safety measures, better land use planning, and public risk communication (Steinberg, Sengul, & Cruz, 2008). Despite these recommendations, the implementation of natech risk reduction policies remains relatively limited (Cruz & Suarez-Paba, 2019, p. 4).

Natech hazards, particularly those involving the release of hazardous substances, have been gaining more attention in the past two decades because of potential implications for environmental justice research. Three such implications of natech events are that the technological after-effects of initial disasters can 1) change the spatial and demographic distribution of harm; 2) extend the harm into the long-term; and 3) introduce complications to environmental justice action like regulation and law suits.

First, some scholars have expressed concern that a decision of whether or not to account for cascading hazards following an initial disaster may significantly alter the results of environmental justice assessments (Picou, 2009). The term “cascading hazards” refers to scenarios in which hazards disrupt other systems, thus contributing directly or indirectly to additional hazards (Cutter, 2018). If risk assessments do not account for plausible cascading hazards, such as chemical releases or dam breaks following a storm, then the potential threat posed to certain areas in the path of the secondary hazard may be underestimated (Menoni, Molinari, Parker, Ballio, & Tapsell, 2012; García-Lopez, 2018). This can be quite challenging for some scenarios, as natech events like chemical releases into the wind or into river systems often result in ‘moving targets’ of exposure that can be hard to model (Fendler, 2008; Rui, Shen, Khalid, Yang, & Wang, 2015). Zhang (2010) found that in the process of buying property, marginalized communities had less access to information about secondary hazard or multihazard risks than wealthier or whiter communities, thereby exacerbating their vulnerability. The author argues that better understanding and communicating the risk of secondary hazards is a critical component of more environmentally just disaster management.

Second, a failure to account for secondary technological hazards can result in an underestimation of the magnitude of harm because situations like chemical releases can extend that harm into the long-term. Chemical exposure and other kinds of technological hazards can introduce slow, 'invisible' harms (e.g., increased risk of cancer following exposure to carcinogens) which continue to affect communities long after the initial triggering event, often creating problematic ambiguity as to who is affected by the initial event (Gill & Ritchie, 2018, pp. 49-50). This is particularly true of the intersection of flooding and hazardous materials, as 'fugitive chemicals' (Madrigano et al., 2018) can be distributed into municipal water sources, soil, crops, and homes, thereby creating a persistent, long-term exposure to hazardous substances (Young et al., 2004; Casteel, Sobsey, & Mueller, 2006; Horney et al., 2018). Effects like these can become integral to 'social cascades' in which a community's repeat exposure to hazards and other environmental stressors over long periods of time can have a 'perverse multiplier effect' on harm and social inequities (Cutter, 2018, pp. 23-24).

Lastly, secondary technological hazards introduce complications to taking action on environmental injustice. With technological hazards removed, the hierarchy of agencies and figures responsible during the disaster management process is relatively well-defined. When natech disasters occur, questions of who is to blame can become murky or ambiguous, creating obstacles to those seeking swift response or accountability (Gill & Ritchie, 2017). For example, the owners of a hazardous facility damaged by a flood can position themselves as victims of an 'act of God' to eschew public outcry or the financial burden of managing a disaster. Without strong natech risk assessment methodologies, it can be difficult to establish when a facility owner is responsible, impeding actions like environmental tort cases (Weeden, 2006). To make matters more challenging, environmental regulations on industries like chemical manufacturing can often be weak, out of date, or otherwise inadequate as a consistent pathway for environmental justice (Madrigano et al., 2018).

### *2.2: Natechs and Environmental Justice in the Southeastern United States*

The history of the southeastern United States has been heavily shaped by social cascades of environmental disaster and has such been incredibly influential in the history of environmental justice. Though it is not unique in its vulnerability to hazards, the region has a long history of high-profile disasters that have highlighted deeply rooted social inequalities by disproportionately impacting marginalized communities (Ermus, 2018). Additionally, the region has historically been characterized by relatively weak environmental regulations and labor laws, creating a political ecology favorable to the siting of facilities that store and process hazardous materials (Bullard, 2000). The intersection of frequent meteorological hazards, a high density of facilities handling hazardous substances, and large numbers of marginalized communities makes the southeastern Unites States a critical theater for the future of natech research.

The environmental justice movement is widely considered to have been born in eastern North Carolina when the planned siting of a landfill for toxic polychlorinated biphenyls (PCBs) was met with protests in 1982 (Bullard, Mohai, Saha, & Wright, 2007). The choice of location, the predominantly Black community of Warrenton, spurred media attention and a report by the United Church of Christ’s Commission for Racial Justice that is considered to be one of the first examples environmental justice research. That report found that the racial composition of communities was the most influential factor in the siting decisions for toxics-handling facilities (UCC, 1987) and led to the executive director of the Commission for Racial Justice, Ben Chavis, coining the term ‘environmental racism’ (Mohai, Pellow, & Roberts, 2009). Bullard (2000) has argued that the systemic disenfranchisement of the southeast United States’ ‘Black Belt’ has created an entire region characterized by low-income rural communities of color that have had limited political resources with which to oppose the siting of potentially hazardous facilities. Twenty years after the UCC study, a longitudinal follow-up concluded that the strength of the relationship between racial composition and the likelihood of toxic facility sitings had increased in that span of time (Bullard et al., 2008).

Though the definition has been criticized as being an oversimplification, the prevailing definition of ‘environmental injustice’ in the literature has come to be the disproportionate placement of environmental disamenities in communities already experiencing social or economic disadvantages (Noonan, 2008). Studies using geographic information systems (GIS) have historically employed one of two main methods to quantify the disproportionate burden of environmental disamenities: *buffer distance*, wherein the hazard posed to a community is represented in terms of its distance from a given source, or *spatial coincidence* (or “host/non-host”), wherein the number or density of hazard sources within the boundaries of an aerial unit (like a county or census tract) is used (Sheppard, Leitner, McMaster, & Tian, 1999). Geographers have long documented that these methods, while fundamental to environmental justice GIS applications, are sensitive to researcher choices in the spatial scale and scope of the units of analysis

(Mennis, 2002). Statistical relationships between socioeconomic variables and the presence of environmental disamenities can shift or seemingly disappear when reexamined at different spatial scales, creating a substantial obstacle for environmental justice researchers. Choices of spatial scale often lack clear ‘right’ answers, and though spatial analysts have refined methodologies for comparing spatial autocorrelation across multiple scales, practical considerations such as the availability of data can often constrain choices of scale regardless (Baden, Noonan, & Turaga, 2007). Thus, it is critical that environmental geographers practice transparency regarding the potential biases that can arise from these choices, particularly in case studies where multi-scalar comparisons cannot be included.

Advancements in understanding the intersection of natech hazards and environmental injustice have largely been spurred by the frequent exposure of the southeastern United States to hurricanes. Flooding- and precipitation-triggered hazardous releases are particularly challenging, as the wide spatial footprint of these events poses the risk of several releases at the same time, making them harder to respond to than non-natech releases (WHO, 2018).The chemical contamination of floodwaters during Hurricane Katrina in 2005 was a critical turning point in bringing together natech research and environmental justice (Weeden, 2006; Cruz & Suarez-Paba, 2019). Measurements of chemical and mold contamination were higher in areas of New Orleans that had higher Black populations (Picou, 2009). A similar spike in natech research followed the particularly severe 2017 Atlantic hurricane season; chemical manufacturing plants in Houston, Texas (Horney et al., 2018) and coal ash dumps in Puerto Rico (Slack et al., 2020) also generated releases that drew the attention of environmental justice scholarship. Because climate change is increasing the risk of severe hurricanes, the southeastern United States is projected to be increasingly prone to such events in the future (Cruz & Suarez-Paba, 2019).

### *2.3: CAFO Risk in Eastern North Carolina*

Swine farming has existed in what is now North Carolina since British colonization of the region in the 1600s. Swine farming was a substantial part of the region's economy throughout the twentieth century, experiencing a period of rapid growth in the 1980s (USDA 1995). In the 1990s, there was an abrupt local shift towards consolidation and centralization of the local supply chain, resulting in fewer, but much larger facilities that came to be regulated as CAFOs (Jones 2006). In 1991, the state senate passed legislation that established expansive local zoning exemptions for industrial swine farms. At the same time, growth in the American pork industry incentivized vertical integration of the industry and the wide-scale consolidation of smaller farms by leading meat producers like Smithfield Foods, Tyson, and Swift & Company (Duke University, 2015). The existing density of small-scale farming operations and the relative lack of zoning regulations made eastern North Carolina attractive for the siting of new CAFOs and other auxiliary facilities, including a meatpacking center in Bladen County that was once the world's largest. During this period of growth, North Carolina became the second-biggest swine producing state in the country, second only to Iowa (Schmidt, 2000).

Swine CAFOs are considered to pose a greater environmental hazard than other types because the dry litter management systems used for other types of livestock are not feasible for swine, necessitating the use of the more flood-vulnerable anaerobic lagoon system (Schmidt, 2000). In 1995, a section of a waste storage lagoon at the Oceanview Farms in Onslow County collapsed, releasing twenty-five million gallons of swine waste into the New River, resulting in fish kills, crop damages, and public outcry ("Huge Spill of Hog Waste," 1995). The same year, the North Carolina Senate passed the Swine Farm Siting Act, imposing siting requirements that prohibited the construction of new waste lagoons or swine houses within a specified minimum distance from private homes, schools, churches, and hospitals. In 1997, public concern over the health risks of swine CAFOs in the state contributed to the establishment of a statewide moratorium on the construction of any facilities with greater than 250 swine or the expansion of any existing CAFOs beyond this limit (Duke University 2015). The moratorium was renewed in 1999 after heavy rainfall during Hurricane Floyd resulted in waste spills from multiple CAFOs in several local watersheds, leading to a state buy-out of several low-lying facilities (Charles 2018).

The moratorium on new CAFOs has continued to the present, being made permanent in 2007 for all farms operating lagoons (NCDEQ, 2016). Though all CAFOs in North Carolina are subject to annual inspections by the North Carolina Department of Environmental Quality (NCDEQ) and are required to procure a certified animal waste management plan (CAWMP), the sheer density of waste in the region continues to pose an environmental and public health challenge (Casteel et al., 2006). The high costs associated with site remediation may result in waste lagoons being left behind for long periods if CAFO operators move or file for insolvency, with many experts having recommended requiring a remediation bonding system when operators seek permits for lagoons (Donham et al., 2007). While natural anaerobic wastewater treatment may minimize the effect of pathogens within a few weeks to months, the waste may not be entirely denitrified and contaminants like heavy metals and latent veterinary pharmaceuticals may remain for longer periods (Burkholder et al., 2007).

### *2.4: CAFOs as Hazards: Public Health and Environmental Justice Literature*

Flooding aside, the adverse effects of exposure to CAFO waste, particularly from swine CAFOs, has been well documented by public health and environmental justice scholars (Nicole 2013). Swine CAFOs emit dense plumes of ammonia, hydrogen sulfide, and fine particulate waste which can impose a pervasive odor on nearby communities (Wing, Horton, & Rose, 2013) and irritate the mucous membranes of the eyes and respiratory system (Wilson & Serre, 2007; Thorne, 2007). Surveys conducted in North Carolina have found that communities surrounding swine CAFOs report experiencing ailments including headache, runny nose, excessive coughing, sore throat, and diarrhea more frequently than nearby control communities, even including those adjacent to non-swine CAFOs (Wing & Wolf, 2000; Bullers 2005). Other physical health conditions found to have similar health linkages include fatigue (Schiffman et al., 1995), hypertension (Wing et al., 2013), and asthma (Mirabelli et al. 2006). A host/non-host study of eastern North Carolina found that cause-specific mortality and hospitalization rates for kidney disease, anemia, septicemia, and low infant birth weight (among others) were higher in zip codes with more than 215 swine per square kilometer (Kravchenko et al., 2018), though this study did not account for occupational exposure and was limited in its capacity to control for demographic variables. Surveys of the region have even reported evidence of mental health impacts from proximity to swine CAFOs, suggesting that prolonged exposure to the odor and fumes contributes to increased reports of stress

(Horton, Wing, Marshall, & Brownley, 2009), depression (Schiffman et al., 1995) and decreased perception of control of one's circumstances (Bullers ,2005) than demographically similar control communities. The link between CAFO fumes and mental health in North Carolina has not been consistent across all studies (cf. Thu et al., 1997).

The potential health hazards of waterborne exposure to swine waste has received less inquiry, but public health scholarship on the region has expressed concern about the potential health impacts of a natech release on the coastal plain (Wing, Freedman, & Band, 2002; Heaney et al., 2015), especially as the populations of these areas tend to experience high rates of poverty and dependence on private wells for drinking water (Jurjonas & Seekamp, 2018; Johnson & Belitz, 2017). In addition to a variety of fecal coliform pathogens (e.g., E. coli, listeria, salmonella) that pose a public health risk even in low concentrations (US EPA, 2015), agricultural waste also often contains high concentrations of phosphates, nitrates, heavy metals, and residual veterinary pharmaceuticals (Sobsey et al., 2006; Burkholder et al., 2007). These pollutants can alter the freshwater ecosystem, not only via the direct mortality of plants and fish, but also by causing sharp fluctuations in the pH and turbidity of the water. Increases in phosphates and nitrates can compromise potability and limit potential uses of river systems through fish die-offs and eutrophication, potentially endangering income through fishing and recreation. A report by the National Association of Local Boards of Health has expressed concern that heightened concentrations of waterborne nitrates from CAFO waste pose a significant public health risk of methemoglobinemia (often known as "Blue Baby Syndrome"), which is often lethal to newborns (Hribar & Schultz, 2010). Unfortunately, while impact of agricultural waste on groundwater needs further study, the private nature of most drinking wells prevents the creation of the precise GIS data, thereby impeding research efforts on the subject (Johnson & Belitz, 2017).

Local experts acknowledged the potential for a large-scale release of swine CAFO waste on the North Carolina Coastal Plain as early as 1999's Hurricane Floyd (Wing et al., 2002). An environmental justice assessment conducted in Iowa by Carrel, Young, and Tate (2016) has argued that better understanding the 'upstream context' of socially-constructed risk and flood hazard is critical for better understanding the risks associated with industrial swine farming (p. 852). Discourse on the vulnerability of CAFOs in eastern North Carolina focuses principally on the extreme precipitation and flooding associated with hurricanes, as these are the most frequent and costly hazards in this part of the state according to the state hazard mitigation plan (NCDPS, 2018). Federal standards for swine feeding operations as established by the National Pollutant Discharge Elimination System (NPDES) require that gravity-fed waste storage lagoons provide "adequate storage to contain a 25-year, 24-hour storm event plus the designed structural freeboard [a minimum of one (1) foot is required]" (NCEMC 2016, p. 4, brackets in original). Predicating design standards on precipitation event return intervals introduces logistical concerns because the threshold magnitudes are subject to shifting baselines and can thus be challenging to model. Even if better models were available, the question still stands as to whether a 25-year return interval is a sufficient standard. Until better design standards and regulations are in place, the sheer number and size of swine CAFOs on the coastal plain warrants concern about natech vulnerability.

# Chapter 3: Data & Pre-Processing

## *3.1: Study Area*

Most of the eastern half of North Carolina overlaps a larger geographic region known as the Atlantic Coastal Plain. Locally, the Atlantic Coastal Plain spans roughly from the Research Triangle (the Raleigh-Durham metropolitan area) to the coast, spanning an area sometimes known locally as the 'Inner Banks.' The abundance of flat, mineral-rich soil has historically made the region popular for growing cotton and tobacco as well as raising livestock. The flat, low-lying topography and high average annual precipitation contribute to a physical geography that is characterized by abundant swamps and marshland with wide, slow-flowing rivers. The region is often exposed to both tropical storms and mid-latitude cyclones which can bring periods of intense precipitation and flooding.

In areas between the Research Triangle, Fayetteville, and the urban developments on the Outer Banks and southeastern coast, the coastal plain has remained an area of low population density. Strong markets for cotton and tobacco prior to the Civil War contributed to a local economic system overwhelmingly dependent on slave labor, forming North Carolina's coastal plain into part of the larger "Black Belt" of the American south. Today, the region's counties have a much higher percentage of Black residents than the national average, and some, such as Warren County, are majority-Black counties. Eastern North Carolina also has one the largest concentrations of Native American population east of the Mississippi River. The Lumbee, Haliwa-Saponi, and

Waccamaw Sioux (among others) have communities in the region. More recently, the rapid growth of industrial agriculture in the region has contributed to an increase in migrant labor from Mexico and Central America. The region also remains very poor with most counties in the region, excluding the Research Triangle and Outer Banks, having median household incomes well below the national average.

The four major river basins on North Carolina's coastal plain (the Cape Fear, the Neuse, the Tar-Pamlico, and the White Oak) serve as the area of analysis (Fig 3.1). Their combined area, consisting of nearly 59,000 $km^2$, contains 1,900 state-licensed swine CAFOs as of February 2019, or about 85% of all such facilities in the state. The choice to focus on these watersheds rather than the entire eastern half of the state was made in an attempt to include as many CAFOs as possible while trying to avoid having an inappropriately large sample of demographic units which might exaggerate the significance of statistical tests. The exclusion of adjacent river basins that cross state boundaries (such as the Lumber-Pee Dee) removes the need to consider different state laws and management regimes for cross-boundary spill events. This area contains Duplin and Sampson Counties, both of which have historically held the title of the largest swine producing counties in the United States (Jones, 2006; Duke University, 2015).

Census block groups (CBGs) were chosen as the unit of analysis to prioritize spatial detail. CBGs that were within or that intersected the area's boundaries were included in their entirety. Counties with populations over 100,000 (Wake, Durham, Guilford, Forsyth, and New Hanover) were excluded as these heavily urbanized areas were all found to have no more than two CAFOs. An exception was made for Cumberland County as it contained 19 swine CAFOs despite containing the city of

Fayetteville and a population of over 100,000. Some CBGs on the Outer Banks (Dare County) were also excluded because they contain no agricultural land and because their separation from the mainland likely renders any potential hazard from potential CAFO spills negligible.

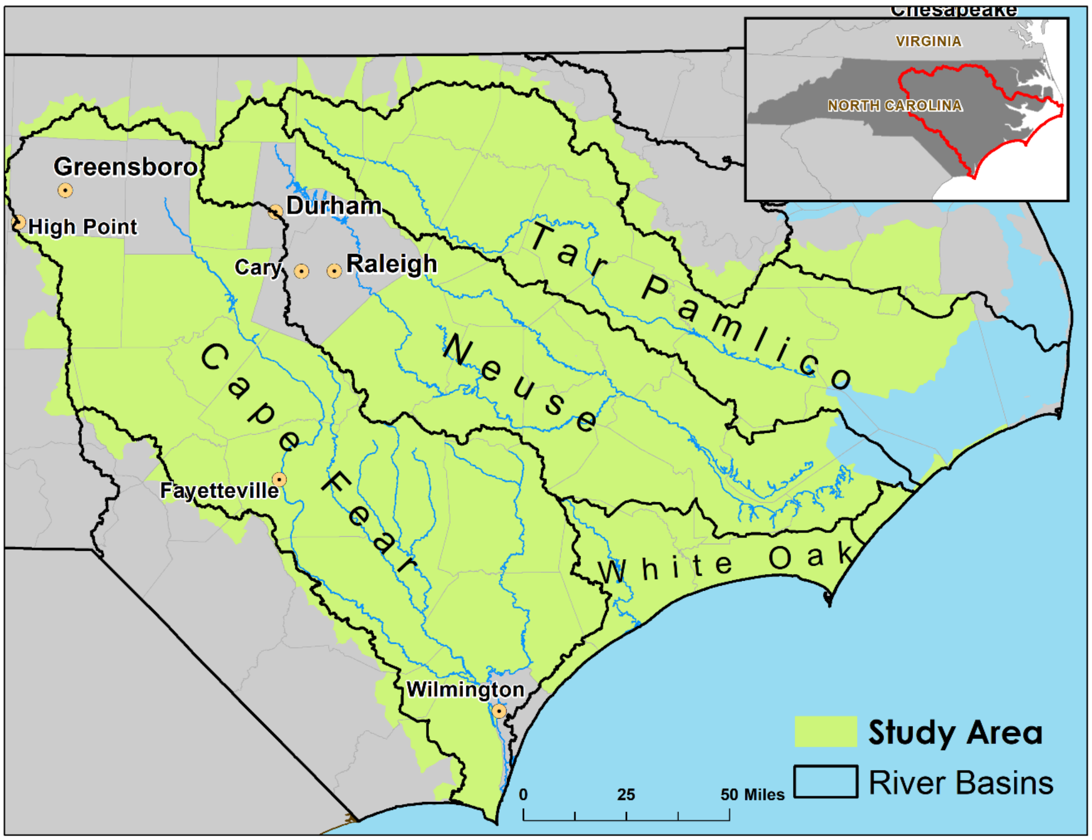


**Figure 3.1:** The study area and major watersheds in eastern North Carolina.

### *3.2: CAFO Risk*

Tabular data on the locations and livestock counts of CAFOs (as of February 2019) were accessed from the NCDEQ, which issues and archives the permits for such facilities (Table 3.1). Latitude-longitude data from these permits were then mapped to create a point-data shapefile of all permitted CAFOs within the state. Facilities that process other types of livestock were excluded to avoid making assumptions about the types of waste management systems being used. Clearly duplicated entries and properties without any listed livestock were also removed. Because the dimensions and safety mechanisms of individual CAFOs are not publicly available, the potential for varying levels of structural integrity at different properties must be excluded here.

Employing the methodology set forth by Carrel, Young, and Tate (2016), this study used animal units (AU) as the proxy for waste output volume. AU is a metric used to standardize estimates of resource use and waste outputs of agricultural facilities across different species and maturities of livestock (Chastain et al., 2003). Definitions of AU for a given species vary somewhat between jurisdictions; values used to represent adult swine vary from 0.2-0.3 (USDA NRCS 1995) to 0.4 (Carrel, Young, & Tate 2016) AU per head. Making the assumption that some feeding operations may contain swine at different levels of maturity, a moderate estimate of 0.3 AU per head was used to account for this potential variation.

The point data was then converted into a raster density surface. Every cell in the grid was given a value by calculating the number of AU per square kilometer within a 2.3km search radius[1] of the cell's centroid, and the average of cell values within each CBG yielded an estimate of the average density of swine AU. This estimate was used to define the technological component (hereinafter "CAFO Risk") of natech risk. Because of the varying size and shape of block groups, representing AU as a density surface is

[1] A search radius of 2.3 km was chosen based on ArcMap's Kernel Density tool, which uses an algorithm to select a default search radius that is resistant to statistical outliers. This default was corroborated against an Incremental Spatial Autocorrelation (ISA) test with one-kilometer increments applied to the CAFO point data using AU as the population field. The results of the ISA suggested that a 2 km radius had the most significant spatial autocorrelation.

necessary for two reasons: inconsistencies in coordinate data and potential boundary problems.

First, comparing the placement of the XY coordinates to a reference map reveals some inconsistencies and practical limitations in the use of point data to represent CAFO properties. The land area of the property is not necessarily indicative of the number of AU housed, and large properties may be represented by coordinates that reflect a central building or farmhouse, rather than the swine houses or waste lagoons. Irregularly shaped properties, properties consisting of non-contiguous parcels, or inconsistencies in the geocoding of rural addresses may all result in coordinates that are slightly offset from the actual locations of the waste ponds. For this reason, it is not practical to define natech risk by the identifying the points that intersect with the floodplain. Aggregating this data into a surface that represents the generalized density of AU, rather than the locations of waste lagoons themselves, helps to correct for some of these inconsistencies.

**Table 3.1:** Risk variable data sources.

| Name | Source | Data Type | Spatial Resolution | Variables | Date |
|---|---|---|---|---|---|
| Swine CAFOs | North Carolina Dept. of Environmental Quality (NCDEQ) | Tabular | Point | Latitude, Longitude, Allowable count (raw count of animals) | Feb. 2019 |
| Flood Zones | Federal Emergency Management Agency (FEMA) | Polygon Shapefile | Sub-County | Zone ID (flood risk category) | Various |

Second, representing the swine distribution data as a density surface helps to correct for certain boundary issues. Representing this information as a density measurement addresses discrepancies in the varying sizes of CBGs. It also addresses the "modifiable areal unit problem" (Holt, Steel, Tranmer, & Wrigley, 1996) in which the interpretation of statistics calculated for spatially aggregated areas is subject to biases stemming from choices in the division of said areas. Because some larger properties may border or cross census boundaries, it is necessary to acknowledge the possibility of CAFO spills potentially falling across multiple jurisdictions. CBGs are relatively small even in sparsely populated rural areas, so a sufficiently large release of a hazardous substance in one is likely to affect its neighbors as well. Without converting AU into a raster, any CBG that is closely surrounded by many CAFOs, but that does not contain any CAFOs itself, would be represented as having no risk. By representing density of swine AU as a gridded surface, points that are close to CBG boundaries can be reflected in the averages for both sides. An overview of this raster preprocessing methodology for ArcGIS software is provided in Fig. 3.2.

### *3.3: Flood Risk*

Flood risk was assessed by overlaying the CBGs with flood risk insurance maps (FIRMs) made available by the North Carolina Floodplain Mapping Program. Though other environmental hazards are relevant to the study area, flooding was prioritized as it is the most pervasive source of risk for CAFOs in the region as per the state hazard mitigation plan (NCDPS, 2016). Though it would be possible to generate a more nuanced representation of flood risk by layering the satellite footprints of prior flooding events to calculate a Poisson probability of flooding (Tate, Cutter, & Berry, 2010), the use of FIRMs maps provides a similar result without additional pre-processing.

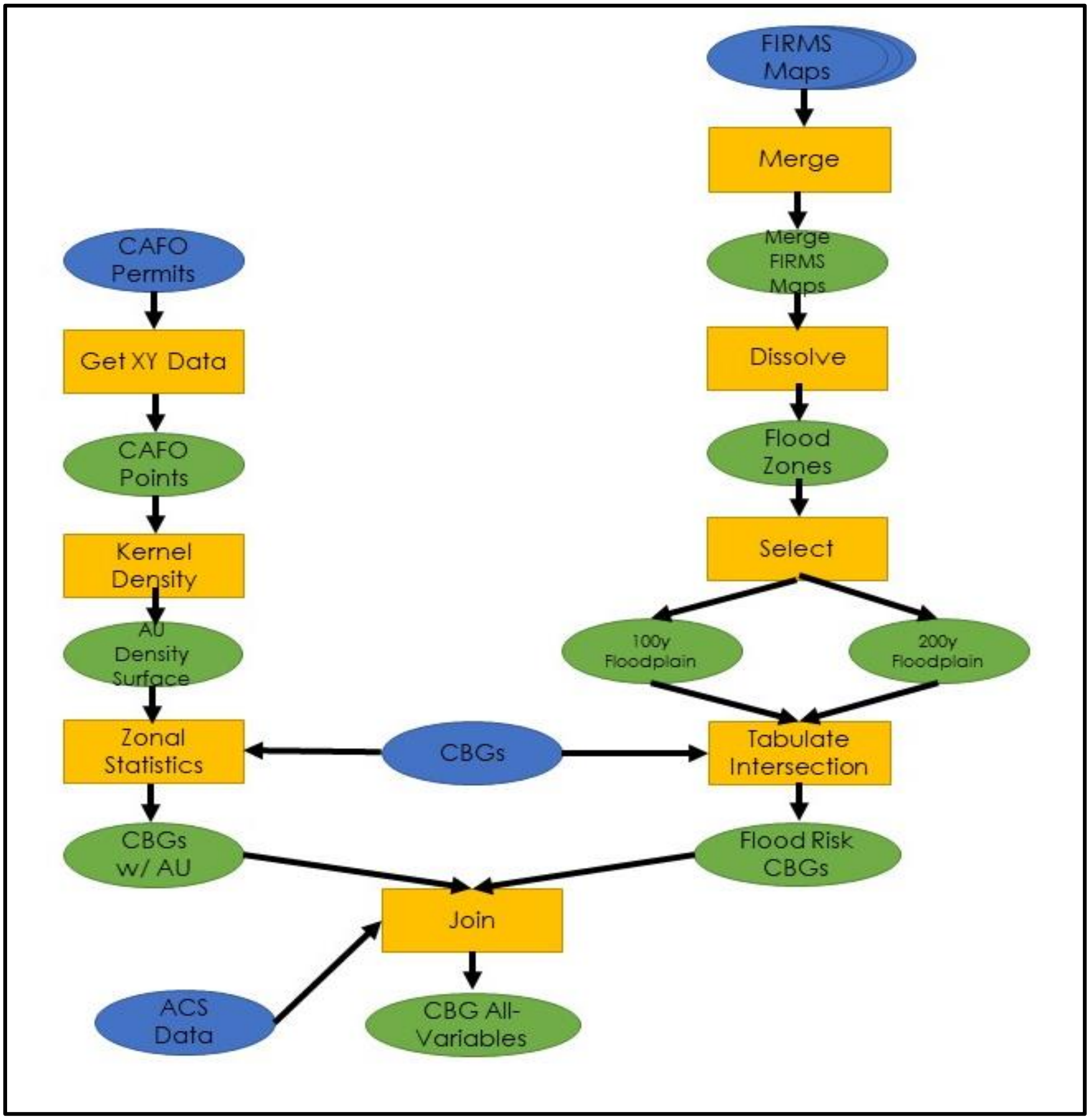


**Figure 3.2:** GIS pre-processing workflow diagram.

To create a flood risk sore for each CBG, the percentage of the area of each CBG that was classified as being within either the 100-year or 200-year floodplain was tabulated in ArcGIS software (Fig. 3.2). Each percentage was then multiplied by the corresponding annual probability of flooding (i.e., 0.01 for the 100-year floodplain and

0.005 for the 200-year floodplain) and added together as a single, generalized score. A CBG entirely within the 100-year floodplain would, for example, be given a flood risk score of 1.0, while a CBG split evenly between the 100-year and 200-year floodplains would yield a score of 0.75 [(50 x 0.01 + 50 x .005) =0.75]. Modelled local estimates of a 25-year, 24-hour precipitation extreme were considered, as the overtopping of lagoons could occur from intense rainfall in the absence of flooding. However, variation in the estimates across the study area was too uniform to effectively differentiate hazard between CBGs. As such, the possibility of intense rainfall in the absence of flooding was noted, but not accounted for in this study.

### *3.4: Environmental Justice*

The selection of environmental justice variables sought to approximate the list of variables included in Social Vulnerability Index, or SoVI (Cutter, Boruff, & Shirley, 2003) with additional variables informed by Carrel, Young, and Tate (2016). All SoVI variables that could be acquired or calculated for the CBG level using the 2017 American Community Survey (ACS) 5-year estimate were included (Table 3.2). The 2017 ACS was selected over the 2010 decennial census in the interest of remaining as up to date as possible. Raw count data was either normalized by the respective unit to get percentages or aggregated into median values where appropriate. A five-year estimate of percent population change was also calculated using 2013 ACS survey data.

**Table 3.2:** Socioeconomic indicator variable names and descriptions

| Variable | Description |
|---|---|
| AGRPC | Percent labor force in agriculture / extractive industries, 2013-2017 |
| AVGPERHH | Average number of persons per household, 2013-2017 |
| CVBRPC | Percent of population participating in the labor force, 2013-2017 |
| EARNDEN | Earnings ($1,000) in all sectors per square km, 2013-2017 |
| FEMLBR | Percent adult female population (16-64) in labor force, 2013-2017 |
| HODENUT | Housing units per square km, 2013-2017 |
| HUVACANT | Percent of housing units that are vacant, 2013-2017 |
| MED_AGE | Median age, 2013-2017 |
| *MEDRENT*[2] | *Median monthly rent asked for renter occupied housing, 2013-2017* |
| *MEDVALOO* | *Median home value for owner occupied housing, 2013-2017* |
| MEDHHI | Median household income, 2013-2017 |
| PCHGPOP | Percent five-year population change, 2013-2017 |
| PCTAPI | Percent Asian or Pacific Islander, 2013-2017 |
| PCTBLACK | Percent Black, 2013-2017 |
| PCTDIS | Percent with a disability, 2013-2017 |
| PCTF_HH | Percent female-headed households (no spouse present), 2013-2017 |
| PCTFEM | Percent female, 2013-2017 |
| PCTHH75 | Percent of households earning <$75,000 annually, 2013-2017 |
| PCTHHNOV | Percent of households without access to a motor vehicle, 2013-2017 |
| PCTHHSSBEN | Percent of households receiving Social Security benefits, 2013-2017 |
| PCTHL | Percent Hispanic or Latinx, 2013-2017 |
| PCTHNOI | Percent of population without health insurance, 2013-2017 |
| PCTHNOWEB | Percent of households without Internet access, 2013-2017 |
| PCTHUNOP | Percent of households lacking adequate plumbing, 2013-2017 |
| PCTKIDS | Percent of population under the age of 5, 2013-2017 |
| PCTMIGRA | Percent foreign born, 2013-2017 |
| PCTMOBL | Percent of housing units that are mobile homes, 2013-2017 |
| PCTNA | Percent Native American or Alaska Native, 2013-2017 |
| PCTNOHS | Percent population 25+ without a high school diploma, 2013-2017 |
| PCTOLD | Percent of population aged 75 and older, 2013-2017 |
| PCTPOV | Percent of population below the poverty line, 2013-2017 |
| PCTRENTER | Percent of housing units occupied by renters, 2013-2017 |
| PCTVLUN | Percent of civilian labor force that is unemployed, 2013-2017 |
| POPDEN | Population density, 2013-2017 |
| SERVPC | Percent of labor force employed in service industries, 2013-2017 |
| TRANPC | Percent labor force in transportation / shipping, 2013-2017 |

[2] Approximately 15% of data values for the median monthly rent and median home value variables were missing from the original ACS dataset and required field imputation. As a rule of thumb, field imputation is generally not advised for any data fields in which greater than 5% of the data have missing values. As such, these two variables are italicized here and in future tables and should be interpreted with caution.

Using ACS data at the CBG level for a rural case study does pose two practical considerations that must be accounted for. First, using the ACS with small aerial units typically results in relatively high margins of error because the ACS employs a smaller sample size than the decennial census. Though the use of the five-year aggregate mitigates this concern, it should be noted that choosing the recency of the ACS over the decennial census will always involve some tradeoff in terms of margins of error. Second, the sparser rural population of the study area means that there is a greater likely of missing values for some variables. This concern was addressed by using geographic imputation to generate an estimate of the missing values. As a rule of thumb, this method of imputation is not advised if the given variable is missing for more than five percent of the total population (Butler & Buckley, 2017). In consideration of this practice, two variables (the median value of owner-occupied homes and the median monthly contract rent of renter-occupied units) were still included, but flagged in all subsequent analyses and should be interpreted with caution. No other variables were missing from more than five percent of the total population, and these values were geographically imputed using the mean values of the adjacent CBGs as an estimate.

# Chapter 4: Methods

### *4.1: Defining "Natech Risk"*

Before it was possible to establish whether or not areas with elevated natech risk are spatially and or demographically different from their surrounding communities, it was first necessary to assess different options for combining the CAFO risk and flood risk variables into a representation of 'natech risk.' While many means for combining these values were possible, this study explored and compared the results of three of the most straightforward methods for quantifying natech hazard as a variable.

First, overlaying CAFO and flood risk into a bivariate map resulted in an *additive* representation of natech risk. This allowed visualization of the differing levels of exposure from the two constituent hazards and categorization of natech risk into high, medium, and low categories. Second, the product of CAFO and flood risk served as a variable (hereinafter 'Natech X') to represent natech risk in a *multiplicative* model. Lastly, calculating z-scores for both CAFO and flood risk and assigning the lesser of the two as a variable to each CBG resulted in a *z-score threshold* model (hereinafter 'Natech Z'). This last method was intended to be more conservative than the Natech X variable when quantifying natech risk for CBGs in which a high outlier for one risk variable might be present with a relatively minor score for the other. This study applied the additive method to provide an intuitive means of visualizing the overlap of the constituent hazards through bivariate mapping. Likewise, the inclusion of the latter two methods provided variables that could quantified and subjected to statistical tests.

To evaluate the utility of the z-score threshold versus the multiplicative models' respective variables and better interpret their results, this study conducted bivariate regressions using Natech X and Natech Z as the dependent variables and CAFO and flood risk independent variables. Comparing the standardized beta coefficients in both tests demonstrated the relative importance of CAFO and flood risk in explaining the variance in each of the two natech variables. If one of the constituent hazards resulted in a much higher beta coefficient than the other, this would be taken into account in the interpretation of the results.

### *4.2: Mapping Natech Risk*

Mapping the overlap of constituent hazards using each of these three methods provided three different ways to visualize the distribution of natech risk and define areas to be considered "high" natech risk. For the additive method, the bivariate map placed divisions at 1 and 2 positive standard deviations above the means of the CAFO and flood risk variables to create a 3x3 categorization. The top-right-most 4 sections (anything for which both CAFO and flood risk were at least 1 standard deviation above their respective means) defined the areas considered to be 'high' risk.

To establish what constitutes 'significant' natech risk for the latter two natech definitions, a Getis-Ord Gi* [pronounced 'G-I-star'] test was conducted on each of the two variables. Gi* tests are a method of measuring local indicators of spatial association (LISA), comparing the spatial distribution of values in a dataset to a theoretically random distribution of the same values within the same geography to identify areas where similar high or low values cluster more than would be expected in a random distribution (Anselin, 1995; Getis, 2008). The Gi* test assigns every unit in a dataset a z-score and p-value indicating the magnitude and statistical significance of clustering, respectively. Due to the varying size and shape of the CBGs, a contiguous neighbor-based conceptualization of spatial relationships was used when carrying out these tests, as recommended by Carrel, Young, and Tate (2016, p. 848).[3]

### *4.3: Assessing Differences Between Natech-Prone and Non-Natech-Prone Areas*

To define three different data subsets to represent high natech risk areas, this study extracted all of the CBGs that were identified as statistically significant hotspots (p-value < 0.1) for each of the Natech X and Natech Z Gi* tests, as well all CBGs in the additive model that were at least 1 standard deviation above the respective means of the constituent hazard variables in the bivariate scheme. The socioeconomic indicator variables of these two subsets, plus the subset consisting of the CBGs in the highest category from the additive bivariate method, were each compared to all other CBGs outside the subset using a two-tailed difference of means t-test assuming unequal variances.

Using a series of difference of means t-tests was favored over an analysis of variance test (ANOVA) test because of the generally unbalanced sample sizes, a likely lack of independence between each of the natech variables, and because of the potential for outlying values and or non-normality, all of which have the potential to introduce

[3] Additionally, a false discovery rate (FDR) correction was applied to reduce the likelihood of any Type I errors at the suggestion of Carrel et al. (2016). Very large datasets or datasets that have a high degree of spatial autocorrelation can often yield high numbers of false discoveries, thereby diminishing the usefulness of the results. Including an FDR correction mitigates this problem by providing a more conservative, adjusted p-value that accounts for the number of data points as well as the higher degree of measured spatial autocorrelation.

significant obstacles to clear interpretation of the results. This series of t-tests made it possible for this study to pursue one of the primary research questions of this study by identifying significant socioeconomic differences between the most natech-prone areas (as measured by each of the three different methods) and the remainder of the study area. Variables identified as significant in two or more of these tests would be taken as characteristic of natech-prone areas, rather than spurious results arising from flaws with one particular natech definition.

With regards to the original research question of whether or not there are characteristics arising only with the strong conjunction of CAFO and flood risk, Pearson's correlation coefficients between each of the four risk variables (CAFO, flood, Natech X, and Natech Z) and the array of socioeconomic indicator variables provided a method for detecting any emergent socioeconomic patterns. To begin, this process was first conducted on the study area as a whole, then for each of the subsets resulting from the three methods of quantifying the risk of a flooding natech. Repeating the Pearson's correlation test with each of the different subsets helped to account for socioeconomic patterns arising at different scales. A resulting table compared the direction, magnitude, and significance of correlation for each variable across each subset of data points. Any characteristics that are both exclusive to natech variables and mostly consistent across methods and scales were taken as evidence of emergent characteristics.

# Chapter 5: Results

To fully understand the geography of CAFO spill risk in eastern North Carolina, it was first necessary to visualize the geographies of the constituent hazards. After mapping CAFO and flood risk to understand their overlap, the next step was to understand how each constituent hazard correlated with socioeconomic indictor variables individually. That knowledge provides valuable context for understanding the patterns that emerge when the natech variables combining those two hazards are subjected to the same correlation tests. Finally, quantifying the differences between the statistically significant hotspots of those natech variables differ from their surrounding areas provides a foothold for assessing whether or not the distribution of potential CAFO spills in the study area places a disproportionate burden on certain demographics, thus constituting an environmental injustice.

## *5.1: Mapping Constituent Hazards*

Though swine CAFOs are found across the region, the highest density of swine AU in eastern North Carolina can be found in the south-central section of the study area (Fig. 5.1). This consists of a large cluster in the Cape Fear River Basin, particularly Sampson and Duplin Counties, as well as a smaller cluster to the northeast in the Neuse River Basin, particularly along Contentnea Creek. CBGs in these clusters are estimated to have more than 200 AU (roughly equivalent to 66 adult swine) of swine per square kilometer. The CBGs in these clusters are generally rural areas, often surrounding small CBGs with low CAFO risk that mark towns and small cities.

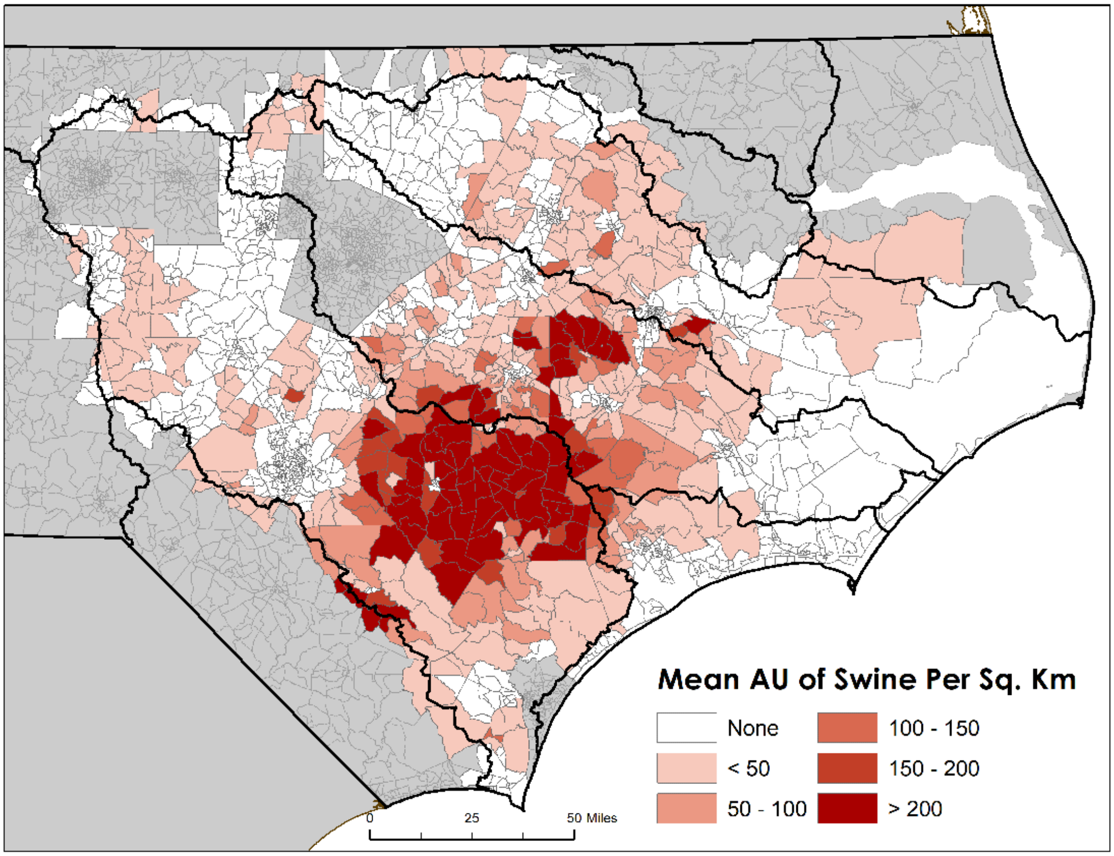


**Figure 5.1:** CAFO risk in the study area, as measured by the average density of swine AU per km$^2$

Flood risk in the study area is generally highest near the coast, with many coastal CBGs consisting almost entirely of designated flood plain (Fig. 5.2). Inland, CBGs along the main stems of the Neuse and Tar Rivers exhibit generally the highest flood risk. The Cape Fear River's main stem, as well as the Northeast Cape Fear River, have more moderate values, but border the region containing the highest CAFO risk. Notably, tributaries of the Cape Fear River Basin that are closer to the center of the main CAFO risk cluster, namely the South and Black Rivers, appear to exhibit relatively low flood risk, though it is possible that the combination of larger overall areas and smaller tributaries in those CBGs obscures the magnitude of flood risk there.

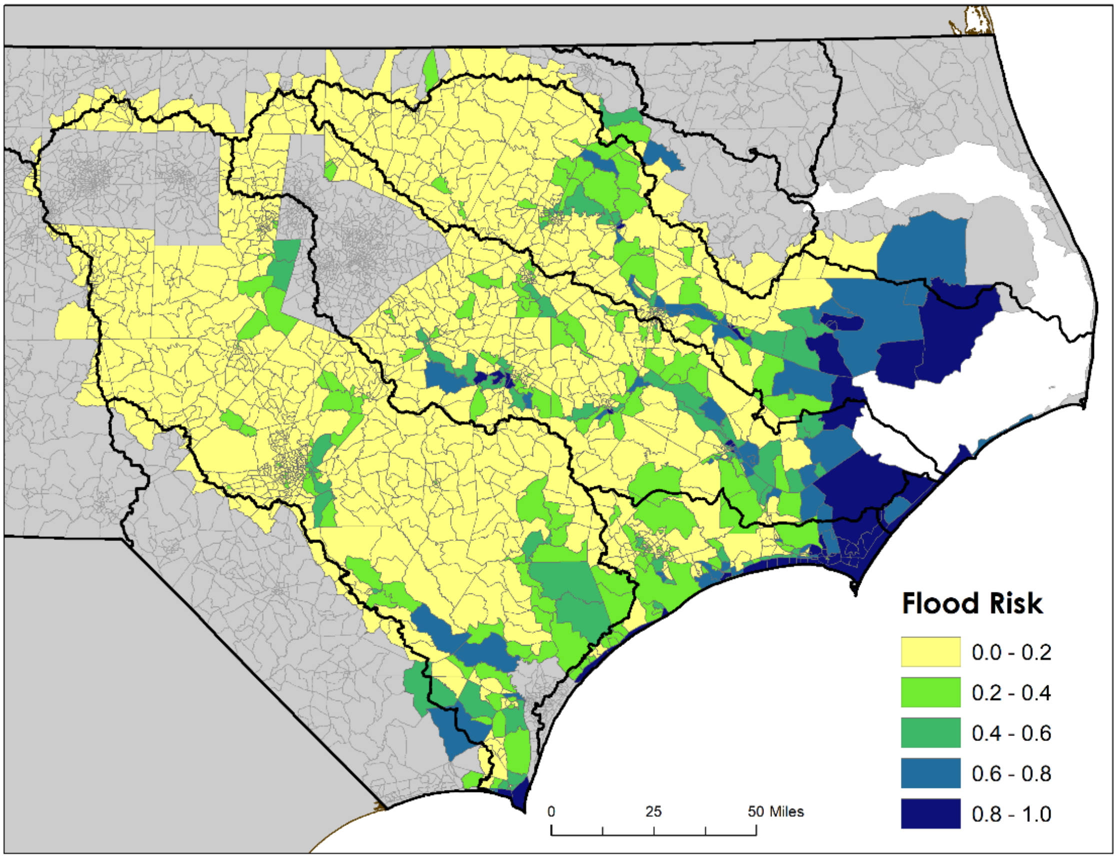


**Fig. 5.2:** Flood risk in the study area, represented as the product of the percentage of a CBG's area that falls within each FEMA flood zone category and the annual probability of flood in the respective zone, such that a CBG falling entirely within the 100-year floodplain receives a score of 1 and a CBG entirely within the 200-year floodplain receives a score of 0.5.

### *5.2 Locating Natech Risk*

When mapped, the additive bivariate method yielded the most conservative results, returning only 17 CBGs that are at least 0.5 standard deviation above the study area means for both CAFO and flood risk (Fig. 5.3). The distribution of CBGs is largely confined to the same areas of high CAFO density as described in Figure 5.1. Within this area, the most common circumstance was the presence of high CAFO risk, but little to no flood risk. Using this method of visualization, areas of substantial natech risk appear relatively few and far between.

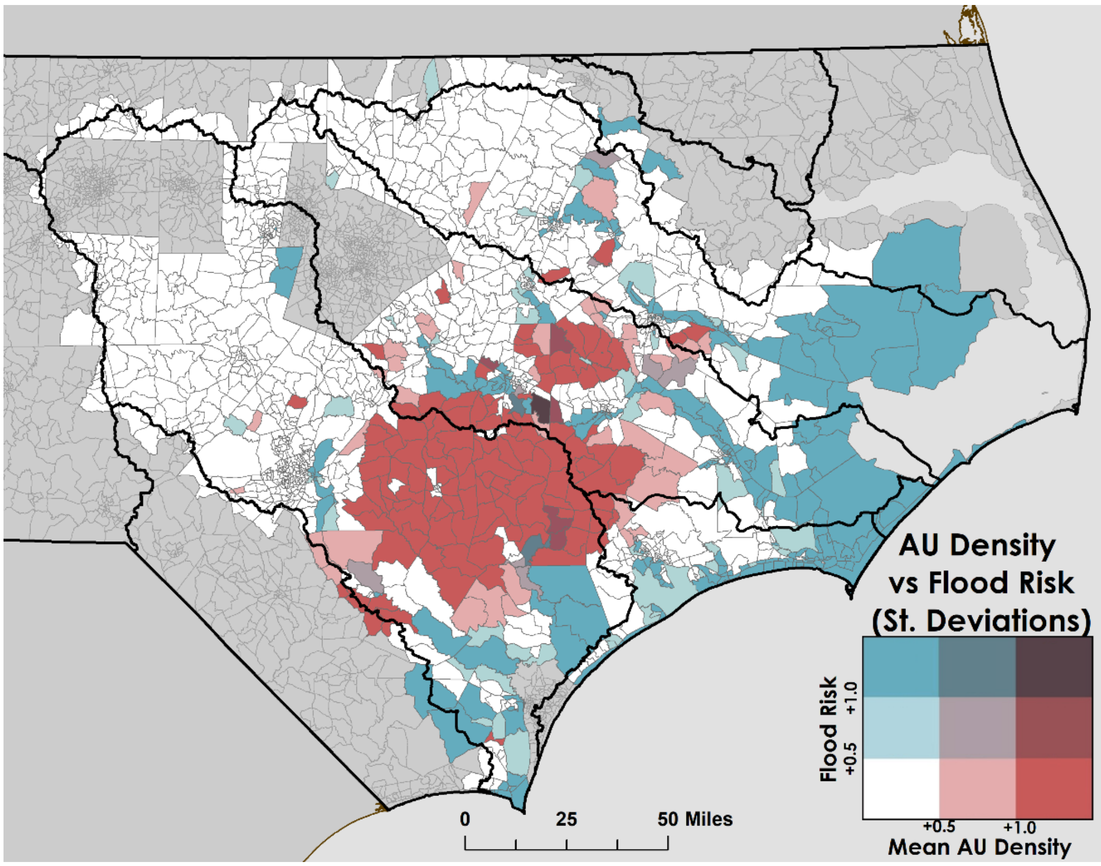


**Figure 5.3:** CAFO risk and flood risk in the study area represented as a bivariate matrix. Category thresholds are set at 0.5 and 1 positive standard deviations above the respective means.

In comparing the other two natech representations, the results of the regression indicated that variance in the Natech X variable was better explained by the constituent hazard variables than was the case for Natech Z (Table 5.1). A tradeoff of this was that for Natech X, the standardized beta coefficient ($\beta$) for CAFO risk was substantially higher than the coefficient for flood risk. Natech Z method had less of an imbalance between the standardized beta coefficients and flood risk exhibited the higher coefficient. In both methods, the adjusted $R^2$ values were relatively weak (< 0.5).

**Table 5.1:** Results of standardized bivariate regressions using Natech X and Natech Z as dependent variables and CAFO and flood risk as independent variables. (N = 1701)

| | **Natech X** | **Natech Z** |
|---|---|---|
| *Multiple R:* | 0.676508 | 0.571024 |
| *$R^2$:* | 0.457663 | 0.326068 |
| *Adjusted $R^2$:* | 0.457024 | 0.325274 |
| *Standard Error:* | 0.737085 | 0.821659 |
| *Intercept:* | -1.4e-07 | 1.61e-05 |
| *CAFO $\beta$:* | 0.658886 ($p < 0.00001$) | 0.29624 ($p < 0.00001$) |
| *Flood $\beta$:* | 0.188091 ($p < 0.00001$) | 0.502534 ($p < 0.00001$) |

Understandably, the distribution of values of the Natech X variable closely resembled the initial distribution of swine CAFOs, more determined by CAFO risk than by flooding. The Natech X variable thus appears more clustered than the Natech Z variable (Fig. 5.4). Despite appearing more spatially diffuse, the Natech Z variable still exhibits several particularly high values in the same region where the highest CAFO risk and Natech X variables appear. It should be noted that interpretation of the Natech Z method may appear counterintuitive, as non-positive z-scores for CAFO and flood risk do not necessarily indicate the absence of said risks, but rather below average risk. As such, negative values greater than approximately -0.32 in the Natech Z method still depict risk, albeit relatively low.

Getis-Ord Gi* tests conducted on the X and Z variables both returned sets of hotspot CBGs that were largely confined to the same regions as the initial density of swine CAFO risk. The hotspots that were found for the Natech X variable were relatively strong and more closely resembled the initial distribution of swine CAFOs, while the Natech Z method returned a noticeably smaller subset of CBGs. In both cases, areas in the central Cape Fear River Basin, primarily around the South River tributary, were flagged as significant hotspots, with smaller hotspots being identified in the Contentnea Creek region of the Neuse River Basin.

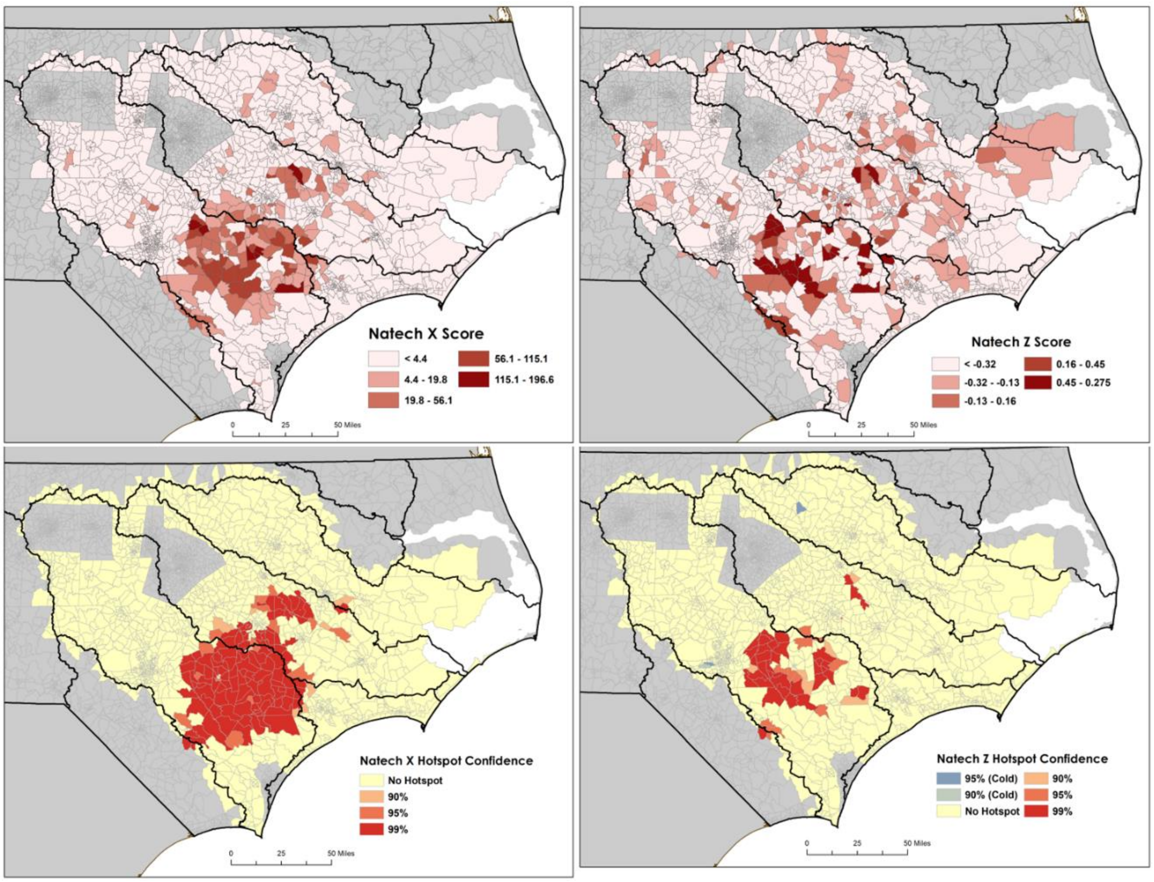


**Figure 5.4:** First row: distribution of the raw variable values for the multiplicative (Natech X, top left) and standardized threshold (Natech Z, top right) variables representing the combination of CAFO and flood risk into natech risk. Second row: results of a Getis-Ord Gi* hotspot test quantifying the significance of spatial autocorrelation of high values of each of the natech variables.

### *5.3: Emergent Socioeconomic Characteristics of Natech Risk*

A greater number of socioeconomic status variables exhibited statistically significant Pearson's correlation coefficients when compared to CAFO risk than they did when compared to any of the hazard variables (Table 5.4). When the whole study area was used as the population for the test, 25 of the variables tested met a threshold of 95% confidence or higher in a two-tailed test, and CAFO risk exhibited a greater number of significant correlations than the other hazard variables in all four groups. The magnitudes of these correlations for the entire study area were generally weak when the whole study area was used, but the correlations often increased when the Gi* hotspots for the Natech X and Z variables were used as the subsets instead. The subset determined by the highest category of the additive bivariate map was not included in this analysis because of its relatively small sample size (n = 17). Variables commonly suggesting low density or rural/agrarian economies (e.g., employment in the agricultural sector or the number of mobile homes) generally had the strongest and most significant correlations with the CAFO risk variable. Across all three groups, CAFO risk generally correlated with increased poverty, lower home values, fewer high-income households, and greater Hispanic populations.

Correlation coefficients between socioeconomic variables and flood risk were relatively common when the whole study area was considered (Table 5.2a) despite being generally weak in magnitude across the board. When it was examined at this scale, the flood risk measurement primarily demonstrated correlations with the age- and race-based demographics, indicating that the areas with the highest flood risk tend to have populations that have higher median ages and have greater percentages of white residents. The number of variables correlating with flood risk dropped off noticeably when more selective subsets were used, as a correlation with inadequate household plumbing was the only statistically significant correlation with the natech variables when either of the two hotspot groups were used.

The Pearson's correlation coefficients measured between the Natech X and Natech Z variables and the socioeconomic indicators (Tables 5.2b-5.2c) were found to mostly be statistically significant, but generally weak in the magnitude of correlation when examined across the entire study area. The number of statistically significant correlations for either of these variables substantially decreased when only the natech hotspot areas were used. When the test was limited to the Natech Z hotspot areas, only the percentage of local households that reported lacking access to basic plumbing had a statistically significant correlation with either natech variable. Furthermore, in both the X and Z groups, none of the statistically significant correlations this study found were unique to the natech variables.

**Table 5.2a:** Pearson's correlation coefficients for the relationships between the hazard variables and socioeconomic indicator variables as measured using the entire study area.

| | **Total** (N=1701) | | | |
|---|---|---|---|---|
| | *CAFO* | *Flood* | *X Variable* | *Z Variable* |
| **AGRPC** | 0.231*** | 0.012 | 0.141*** | 0.074** |
| **AVGPERHH** | 0.090*** | -0.088*** | 0.050* | 0.001 |
| **CVBRPC** | -0.028 | 0.000 | -0.042 | 0.002 |
| **EARNDEN** | -0.180*** | -0.044 | -0.121*** | -0.100*** |
| **FEMLBR** | -0.111*** | -0.029 | -0.087*** | -0.074** |
| **HODENUT** | -0.191*** | -0.021 | -0.127*** | -0.102*** |
| **HUVACANT** | -0.108*** | -0.066** | -0.070** | -0.082*** |
| **MED_AGE** | 0.002 | 0.114*** | -0.001 | 0.060* |
| **MEDHHI** | -0.092*** | 0.019 | -0.068** | -0.033 |
| ***MEDRENT*** | *-0.194**** | *0.022* | *-0.134**** | *-0.076*** |
| ***MEDVALOO*** | *-0.178**** | *0.117**** | *-0.126**** | *-0.050** |
| **PCHGPOP** | 0.008 | -0.021 | -0.008 | -0.043 |

| | | | | |
|---|---|---|---|---|
| **PCTAPI** | -0.098*** | -0.027 | -0.064** | -0.048* |
| **PCTBLACK** | -0.029 | -0.097*** | -0.008 | -0.062* |
| **PCTDIS** | 0.114*** | 0.038 | 0.074** | 0.044 |
| **PCTF_HH** | -0.062* | -0.036 | -0.036 | -0.049* |
| **PCTFEM** | 0.011 | 0.120*** | 0.001 | 0.064** |
| **PCTHH75** | -0.120*** | 0.047 | -0.093*** | -0.052* |
| **PCTHHNOV** | -0.035 | -0.017 | -0.008 | -0.031 |
| **PCTHHSSBEN** | 0.051* | 0.090*** | 0.031 | 0.053* |
| **PCTHL** | 0.197*** | -0.077** | 0.113*** | 0.012 |
| **PCTHNOI** | 0.061* | 0.000 | 0.028 | 0.008 |
| **PCTHNOWEB** | 0.108*** | -0.033 | 0.048* | 0.020 |
| **PCTHUNOP** | -0.011 | -0.016 | 0.037 | 0.038 |
| **PCTKIDS** | -0.005 | -0.059* | 0.016 | -0.020 |
| **PCTMIGRA** | -0.132*** | -0.057* | -0.097*** | -0.105*** |
| **PCTMOBL** | 0.325*** | 0.003 | 0.190*** | 0.119*** |
| **PCTNA** | -0.006 | 0.021 | -0.003 | 0.006 |
| **PCTNOHS** | 0.108*** | -0.008 | 0.087*** | 0.065** |
| **PCTOLD** | -0.026 | 0.103*** | 0.001 | 0.048* |
| **PCTPOV** | 0.075** | -0.035 | 0.048* | -0.010 |
| **PCTRENTER** | -0.127*** | -0.040 | -0.078** | -0.081*** |
| **PCTVLUN** | -0.004 | 0.007 | -0.020 | -0.022 |
| **POPDEN** | -0.180*** | -0.035 | -0.120*** | -0.105*** |
| **SERVPC** | -0.056* | 0.000 | -0.042 | -0.042 |
| **TRANPC** | 0.105*** | -0.054* | 0.077** | 0.066** |
| **Statistical significance: * p < 0.05; ** p < 0.01; *** p < 0.001** | | | | |

**Table 5.2b:** Pearson's correlation coefficients for the relationships between the hazard variables and socioeconomic indicator variables as measured using Census Block Groups falling within the Getis-Ord hotspots of the Natech X variable.

| | **Natech X Hotspots** (N=142) | | | |
|---|---|---|---|---|
| | *CAFO* | *Flood* | *X Variable* | *Z Variable* |
| **AGRPC** | 0.189* | -0.121 | 0.042 | -0.064 |
| **AVGPERHH** | 0.191* | -0.120 | 0.035 | -0.098 |
| **CVBRPC** | 0.085 | -0.135 | -0.088 | -0.084 |
| **EARNDEN** | -0.271** | -0.070 | -0.197* | -0.118 |
| **FEMLBR** | -0.074 | -0.005 | -0.069 | -0.051 |
| **HODENUT** | -0.321*** | 0.014 | -0.135 | -0.030 |
| **HUVACANT** | -0.025 | 0.075 | 0.038 | 0.011 |
| **MED_AGE** | -0.047 | -0.015 | -0.030 | -0.001 |
| **MEDHHI** | -0.118 | -0.051 | -0.120 | -0.078 |
| ***MEDRENT*** | *-0.201** | *-0.059* | *-0.160* | *-0.091* |
| ***MEDVALOO*** | *-0.328**** | *-0.101* | *-0.200** | *-0.124* |
| **PCHGPOP** | 0.009 | -0.142 | -0.076 | -0.137 |
| **PCTAPI** | -0.072 | -0.074 | -0.074 | -0.072 |

| | | | | |
|---|---|---|---|---|
| **PCTBLACK** | 0.009 | 0.134 | 0.091 | 0.085 |
| **PCTDIS** | 0.077 | -0.116 | 0.016 | -0.025 |
| **PCTF_HH** | -0.085 | 0.090 | 0.029 | 0.074 |
| **PCTFEM** | -0.063 | 0.002 | -0.061 | -0.022 |
| **PCTHH75** | -0.202* | -0.151 | -0.217** | -0.141 |
| **PCTHHNOV** | 0.036 | 0.086 | 0.160 | 0.114 |
| **PCTHHSSBEN** | 0.003 | -0.040 | -0.034 | -0.066 |
| **PCTHL** | 0.256** | -0.098 | 0.069 | -0.057 |
| **PCTHNOI** | 0.036 | -0.109 | -0.054 | -0.109 |
| **PCTHNOWEB** | 0.034 | -0.082 | -0.054 | -0.093 |
| **PCTHUNOP** | -0.002 | 0.191* | 0.244** | 0.262** |
| **PCTKIDS** | -0.022 | 0.029 | 0.072 | 0.036 |
| **PCTMIGRA** | -0.221** | -0.127 | -0.201* | -0.175* |
| **PCTMOBL** | 0.267** | -0.159 | -0.057 | -0.163 |
| **PCTNA** | -0.003 | 0.057 | 0.030 | 0.054 |
| **PCTNOHS** | 0.109 | 0.080 | 0.058 | 0.048 |
| **PCTOLD** | -0.072 | 0.063 | 0.067 | 0.092 |
| **PCTPOV** | 0.261** | -0.039 | 0.132 | 0.017 |
| **PCTRENTER** | -0.079 | 0.112 | 0.050 | 0.060 |
| **PCTVLUN** | 0.016 | -0.034 | -0.102 | -0.103 |
| **POPDEN** | -0.325*** | -0.003 | -0.167* | -0.076 |
| **SERVPC** | -0.057 | 0.007 | -0.039 | -0.032 |
| **TRANPC** | -0.024 | -0.048 | -0.048 | -0.034 |
| **Statistical significance: * p < 0.05; ** p < 0.01; *** p < 0.001** | | | | |

**Table 5.2c:** Pearson's correlation coefficients for the relationships between the hazard variables and socioeconomic indicator variables as measured using Census Block Groups falling within the Getis-Ord hotspots of the Natech Z variable.

| | **Natech Z Hotspots** (N=56) | | | |
|---|---|---|---|---|
| | *CAFO* | *Flood* | *X Variable* | *Z Variable* |
| **AGRPC** | 0.286* | -0.142 | 0.021 | -0.076 |
| **AVGPERHH** | 0.099 | -0.058 | 0.014 | -0.043 |
| **CVBRPC** | -0.055 | -0.114 | -0.174 | -0.106 |
| **EARNDEN** | -0.385** | -0.039 | -0.212 | -0.101 |
| **FEMLBR** | 0.065 | -0.033 | 0.023 | -0.013 |
| **HODENUT** | -0.348** | -0.042 | -0.165 | -0.083 |
| **HUVACANT** | 0.076 | 0.083 | 0.152 | 0.077 |
| **MED_AGE** | 0.048 | -0.067 | -0.039 | -0.063 |
| **MEDHHI** | -0.150* | 0.034 | -0.103 | -0.019 |
| ***MEDRENT*** | *-0.338*** | *0.109* | *-0.026* | *0.087* |
| ***MEDVALOO*** | *-0.344* | *0.049* | *-0.138* | *0.025* |
| **PCHGPOP** | 0.108 | -0.107 | -0.057 | -0.128 |
| **PCTAPI** | -0.046 | -0.027 | -0.144 | -0.115 |
| **PCTBLACK** | 0.079 | -0.079 | 0.073 | -0.011 |
| **PCTDIS** | 0.257 | -0.144 | -0.010 | -0.110 |

| | | | | |
|---|---|---|---|---|
| **PCTF_HH** | -0.116 | 0.008 | 0.007 | 0.013 |
| **PCTFEM** | 0.115 | -0.046 | 0.018 | -0.012 |
| **PCTHH75** | -0.358** | -0.004 | -0.238 | -0.058 |
| **PCTHHNOV** | 0.160 | -0.027 | 0.129 | 0.029 |
| **PCTHHSSBEN** | 0.072** | -0.002 | 0.071 | 0.006 |
| **PCTHL** | 0.393 | -0.251 | -0.028 | -0.211 |
| **PCTHNOI** | -0.019 | -0.258 | -0.215 | -0.231 |
| **PCTHNOWEB** | 0.144 | -0.097 | 0.033 | -0.053 |
| **PCTHUNOP** | -0.125 | 0.391** | 0.316* | 0.341* |
| **PCTKIDS** | -0.007 | 0.157 | 0.181 | 0.160 |
| **PCTMIGRA** | -0.368** | 0.038 | -0.249 | -0.131 |
| **PCTMOBL** | 0.490*** | 0.001 | 0.135 | -0.006 |
| **PCTNA** | 0.005 | -0.055 | -0.095 | -0.071 |
| **PCTNOHS** | -0.124 | 0.034 | -0.030 | 0.000 |
| **PCTOLD** | 0.006 | 0.112 | 0.167 | 0.141 |
| **PCTPOV** | 0.290* | -0.059 | 0.093 | -0.025 |
| **PCTRENTER** | 0.041 | 0.105 | 0.151 | 0.089 |
| **PCTVLUN** | 0.040 | -0.141 | -0.153 | -0.160 |
| **POPDEN** | -0.334* | -0.051 | -0.166 | -0.091 |
| **SERVPC** | -0.127 | 0.030 | -0.033 | -0.015 |
| **TRANPC** | -0.221 | -0.069 | -0.136 | -0.066 |
| **Statistical significance: * p < 0.05; ** p < 0.01; *** p < 0.001** | | | | |

*5.4: Demographic Characteristics of Natech Hotspots*

In addition to the geographical agreement between the three methods of defining natech risk, the difference of means t-tests conducted on each of the three configurations also agree on certain economic and demographic differences between the CBGs within the Gi* hotspots of each of the natech variables and the rest of the study area (Table 5.3). Indicators of density showed the starkest differences: the densities of population, housing units, and combined earnings all had extremely high t-values and surpassed the highest threshold of statistical significance in all three tests. Similarly, variables associated with urbanity versus rurality also demonstrated high-magnitude, high-significance differences. In the Natech X and Natech Z hotspots, the percentages of people employed in agricultural/extractive sectors (approximately 12 and 11%, respectively) and transportation/materials moving sectors (approximately 10 and 11%) were significantly higher than in surrounding areas: for the study area as a whole, each sector employed about 7% of the civilian labor force (Table 5.4).

Indicators of economic wellbeing also showed strong differences. The three subsets all appeared to have lower median household incomes and much fewer households with combined annual incomes in excess of $75,000. The Natech X and Z hotspots both exhibited much higher poverty than the rest of the study area, but this was only found to be statistically significant within the Natech X hotspot. The findings also suggested that the number of recipients of Social Security benefits was significantly higher in the highest bivariate category and the natech variables hotspots. Similarly, the percentage of households without health insurance was significantly lower in these subset areas. Indicators of the job market were less clear-cut. While the Natech X and Z hotspots indicated that lower percentages of their populations (particularly their female populations) were in the civilian labor force than was the case for the surrounding areas, these were only significant in the Natech X hotspot. Notably, while the rate of unemployment reported did not exhibit a clear distinction between the subset areas and the study area as a whole, the percentage of people aged 25 and older who lack high school diplomas was significantly higher in these areas.

The quality of housing conditions generally appeared to be lower for the areas in the hotspots and high bivariate category, though this was not true of all variables. Home values and reported contract rent asked both appeared to be far lower in these areas, though it should be noted that the strength of the results for those two tests may be shaped by a high number of imputed values in those datasets. The ratio of home renters to owners appeared to be much lower, though this may simply be characteristic of the region’s rurality. Tests generally agreed that there was a lower percentage of vacant housing units, but also that a much higher percentage of the housing stock consisted of mobile homes in these areas. The percentage of households lacking internet access appeared to be lower in the subset areas but was only found to be significant in the Natech X hotspot, though access to vehicles and indoor plumbing did not appear to exhibit a clear difference.

**Table 5.3:** Results of two-sample difference of means t-tests between natech risk hotspots found using three different methodologies and the remainder of the study area

| | **Bivariate** (n = 17) | **Natech X** (n = 142) | **Natech Z** (n = 56) |
|---|---|---|---|
| AGRPC | 1.167 | 7.050 *** | 2.853 ** |
| AVGPERHH | 0.712 | 3.187 ** | 1.741 |
| CVBRPC | 0.130 | -2.772 ** | -1.521 |
| EARNDEN | -6.215 *** | -23.427 *** | -20.858 *** |
| FEMLBR | 0.114 | -3.875 *** | -1.863 |
| HODENUT | -7.938 *** | -24.640 *** | -19.211 *** |
| HUVACANT | -0.661 | -6.853 *** | -4.975 *** |
| MED_AGE | -0.143 | 0.577 | 0.989 |
| MEDHHI | -1.479 | -6.241 *** | -3.318 ** |
| *MEDRENT* | *-1.429* | *-15.049* *** | *-13.746* *** |
| *MEDVALOO* | *-2.447* * | *-14.236* *** | *-14.455* *** |
| PCHGPOP | -1.676 | 0.343 | -1.317 |
| PCTAPI | -2.411 * | -6.370 *** | -7.058 *** |
| PCTBLACK | -0.119 | -0.997 | -0.053 |
| PCTDIS | 0.003 | 4.780 *** | 2.883 ** |
| PCTF_HH | 1.396 | -2.320 * | -1.823 |
| PCTFEM | -0.180 | 1.274 | 0.612 |
| PCTHH75 | -1.399 | -6.682 *** | -4.382 *** |
| PCTHHNOV | 0.148 | -1.399 | -0.295 |
| PCTHHSSBEN | -0.687 | 3.287 ** | 2.155 * |
| PCTHL | 1.462 | 5.120 *** | 2.300 * |
| PCTHNOI | -0.114 | 2.669 ** | 2.056 * |
| PCTHNOWEB | 1.681 | 3.678 *** | 1.020 |
| PCTHUNOP | 3.471** | -2.013 * | -0.662 |
| PCTKIDS | -0.827 | -0.054 | -0.261 |
| PCTMIGRA | -2.759 * | -10.440 *** | -14.731 *** |
| PCTMOBL | 3.372 ** | 14.322 *** | 6.964 *** |
| PCTNA | -3.000 ** | -0.826 | 1.031 |
| PCTNOHS | 0.373 | 3.707 *** | 3.681 *** |

| | | | |
|---|---|---|---|
| PCTOLD | -0.357 | -0.614 | -0.138 |
| PCTPOV | 1.524 | 2.665 ** | 1.022 |
| PCTRENTER | -2.643* | -8.635 *** | -5.511 *** |
| PCTVLUN | 0.944 | 0.117 | -1.568 |
| POPDEN | -6.673*** | -23.301 *** | -17.688 *** |
| SERVPC | 0.178 | -1.989 * | -1.550 |
| TRANPC | 1.498 | 4.692 *** | 3.243 ** |
| **Statistical significance: * p < 0.05; ** p < 0.01; *** p < 0.001** | | | |

**Table 5.4:** Comparison of socioeconomic variables between the total study area and the three subsets representing natech risk

| | **TOTAL** (N = 1701) | | **BIVARIATE** (n = 17) | | **NATECH X** (n = 142) | | **NATECH Z** (n = 56) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | S Dev | Mean | S Dev | Mean | S Dev | Mean | S Dev |
| AGRPC | 7.0 | 7.1 | 9.1 | 7.2 | 11.8 | 8.7 | 10.7 | 10.0 |
| AVGPERHH | 2.5 | 0.5 | 2.7 | 0.5 | 2.6 | 0.4 | 2.6 | 0.4 |
| CVBRPC | 48.1 | 10.0 | 47.7 | 6.7 | 46.4 | 7.6 | 46.6 | 7.6 |
| EARNDEN* | 61 | 97 | 0.6 | 0.5 | 0.6 | 0.6 | 0.6 | 0.9 |
| FEMLBR | 49.6 | 10.2 | 46.9 | 5.2 | 46.4 | 10.2 | 47.0 | 10.4 |
| HODENUT* | 17 | 26 | 19 | 16 | 17 | 15 | 20 | 38 |
| HUVACANT | 31.6 | 20.0 | 25.1 | 14.7 | 25.0 | 11.1 | 22.8 | 13.2 |
| MED_AGE | 40.1 | 9.5 | 38.2 | 4.2 | 40.4 | 7.3 | 41.0 | 6.8 |
| MEDHHI | 47 | 19 | 45 | 10 | 41 | 11 | 43 | 10 |
| *MEDRENT* | *618.5* | *247.5* | *475.3* | *99.9* | *458.3* | *116.3* | *445.0* | *86.2* |
| *MEDVALOO** | *143* | *82* | *88* | *13* | *100* | *31* | *93* | *23* |
| PCHGPOP | 4.6 | 28.2 | -7.5 | 22.4 | 5.4 | 28.6 | 0.2 | 25.4 |
| PCTAPI | 1.5 | 3.4 | 0.3 | 0.7 | 0.5 | 1.7 | 0.4 | 1.0 |
| PCTBLACK | 28.0 | 24.0 | 23.8 | 15.0 | 26.6 | 17.0 | 27.9 | 20.0 |
| PCTDIS | 15.4 | 8.7 | 14.3 | 4.4 | 18.5 | 8.1 | 18.5 | 8.2 |
| PCTF_HH | 6.7 | 7.1 | 6.0 | 5.2 | 5.7 | 4.8 | 5.4 | 5.1 |
| PCTFEM | 41.6 | 10.1 | 40.7 | 4.5 | 42.5 | 8.6 | 42.2 | 7.3 |
| PCTHH75 | 21.1 | 13.2 | 15.6 | 8.7 | 16.5 | 8.0 | 16.5 | 7.6 |
| PCTHHNOV | 6.7 | 9.2 | 4.2 | 5.9 | 5.9 | 6.3 | 6.3 | 8.2 |
| PCTHHSSBE | 35.0 | 14.1 | 34.2 | 9.0 | 37.9 | 10.5 | 37.8 | 9.6 |
| PCTHL | 9.4 | 10.8 | 14.5 | 16.0 | 15.5 | 15.3 | 14.1 | 15.8 |
| PCTHNOI | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 |
| PCTHNOWEB | 0.2 | 0.1 | 0.3 | 0.1 | 0.3 | 0.2 | 0.3 | 0.1 |
| PCTHUNOP | 2.7 | 4.2 | 4.3 | 4.5 | 2.3 | 2.7 | 2.5 | 3.3 |
| PCTKIDS | 6.0 | 4.0 | 7.0 | 3.5 | 6.0 | 3.6 | 5.8 | 3.7 |
| PCTMIGRA | 2.9 | 5.9 | 0.1 | 0.2 | 0.7 | 2.1 | 0.2 | 0.9 |
| PCTMOBL | 18.9 | 18.2 | 33.3 | 14.3 | 36.3 | 14.9 | 33.2 | 15.6 |
| PCTNA | 0.9 | 3.0 | 0.1 | 0.3 | 0.8 | 1.7 | 1.1 | 2.0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| PCTNOHS | 24.5 | 9.4 | 27.7 | 10.1 | 27.0 | 8.1 | 29.3 | 9.9 |
| PCTOLD | 16.7 | 9.0 | 16.0 | 5.2 | 16.4 | 6.2 | 16.6 | 6.1 |
| PCTPOV | 19.5 | 14.5 | 19.5 | 7.5 | 21.9 | 11.1 | 21.1 | 12.0 |
| PCTRENTER | 31.1 | 22.9 | 23.0 | 13.4 | 22.5 | 10.9 | 21.3 | 13.1 |
| PCTVLUN | 9.2 | 7.9 | 7.0 | 5.0 | 9.3 | 6.2 | 8.0 | 5.9 |
| POPDEN | 371.1 | 586.3 | 42.2 | 33.2 | 40.2 | 35.3 | 45.9 | 92.1 |
| SERVPC | 19.5 | 10.6 | 19.9 | 6.7 | 18.1 | 8.4 | 17.6 | 9.2 |
| TRANPC | 7.1 | 6.7 | 8.5 | 5.3 | 9.7 | 7.1 | 10.6 | 8.4 |

***In thousands**

Any demographic differences that might exist between highly natech-prone areas and their surroundings were not as well-defined or clearly visible in these results. In general, the racial composition of the natech risk hotspot areas typically featured higher percentages of the local population that identified as being either Hispanic or Latinx, but much lower percentages of Asians and Pacific Islander populations or people who reported as being born outside of the United States. The percentages of the population identifying as being either Black or Native American did not appear to have any significant difference between the hotspot areas and the remainder of the study area. Similarly, median age or the percentages of respondents in different age brackets did not appear to be appreciably different from the study area as a whole. On the other hand, the percentage of the local population identifying as having a disability was, however, significantly higher in the Natech X and Z hotspot areas than it was for the remainder of the study area.

# Chapter 6: Discussion and Conclusion

This case study sought to explore how traditional indicators of environmental justice behave in natech risk scenarios by measuring patterns in socioeconomic indicator variables in the co-presence of environmental and technological hazards. This study outlined multiple methods for defining and mapping the overlap of flood risk and swine CAFO density in eastern North Caroline, then tested whether the socioeconomic conditions of areas meeting different definitions of significant overlap of the two hazards were demonstrably different from those of surrounding areas. Along the way, the possibility of socioeconomic patterns emergent only in the presence of both constituent hazards was also questioned. Additive, bivariate mapping and two constructed natech proxy variables all suggested that rural communities along key tributaries of the Cape Fear and Neuse River Basis were at the greatest risk of a flood-triggered CAFO waste release natech. At the census block group scale, these three representations of natech risk suggested that areas with significant overlap of constituent hazards were more economically vulnerable than the surrounding region. However, the study did not detect any emergent socioeconomic conditions that were uniquely correlated to the co-presence of both flooding and high CAFO density.

## *6.1: Discussion*

Based on the results of these methods, natech risk primarily affects the central Cape Fear River Basin, namely eastern Sampson County, as well as some smaller sections of the neighboring Neuse River Basin. Preliminary mapping suggested that the highest CAFO risk is more confined to these two river basins and that flood risk is more broadly distributed across the study area. The presence of several extremely large swine CAFOs in this area likely explains the heavy clustering in the Cape Fear River Basin. Sampson County contains several of North Carolina’s largest CAFOs and contains the highest density of swine in the state, serving both spatially and functionally as a center for the North Carolina pork industry.

Though the Gi* test for the Natech X proxy variable returned a much larger subset of CBGs whose distribution was indicative of the greater weight given to CAFO risk over flooding, the hotspots resulting from the more balanced Natech Z proxy variable provided a conservative estimate of the distribution of high natech risk. Many of the CBGs flagged by the bivariate mapping or the Natech Z hotspot group were not situated on the main stems of their respective river basins, but rather on mid-size tributaries such as the South River, Black River, and Contentea Creek. These are all swampy watersheds with wide and relatively flat floodplains, and these smaller tributaries may be prone to faster changes in river height during high precipitation events than main stem rivers. While large swine CAFOs are not often sited in close proximity to main waterways, these mid-size tributaries are more common and may not be as well protected by environmental regulation or public awareness as larger riverways. The Natech Z hotspot results suggest that the biggest concern for natech events might be communities adjacent to primary and secondary tributaries, rather than those adjacent to main stem rivers.

Difference of means t-tests provided evidence that these areas of overlap were significantly more economically vulnerable than their surrounding areas. While many of the strongest and most significant results were simple measures of density or intuitive characteristics of agrarian economies, a higher degree of economic vulnerability in these areas was suggested by lower median household incomes, a relative lack of high-income households, a higher rate of adults without high school diplomas, and a higher share of households without health insurance plans. These trends were significant despite the abundance of rural agrarian CBGs in the study area as a whole, suggesting that these natech hotspot communities may be particularly economically vulnerable.

For this scale of analysis, these findings did not corroborate previous studies that found that predominantly Black communities and communities with lower adult educational attainment were disproportionately affected by the siting of swine CAFOs. However, previous studies addressing this question focused on a more limited number of socioeconomic variables and used either a different case study (Carrel et al., 2016) or a different scale of analysis and different methodology for defining the impacted area (Wing et al., 2002). This study *did* indicate that areas with higher natech risk contained significantly greater percentages of people identifying as Hispanic or as having a disability. Because some of the discrepancies between this study and previous findings might be explained by differences in the unit of aggregation or in the breadth of the study area as a whole, the results of this study should not be interpreted as conclusive or comprehensive evidence against the presence of environmental injustice in North Carolina coastal plain.

Because CAFO risk was not distributed as broadly across the study area as flood risk, it is likely that the communities exposed to flooding are far less homogenous than those exposed to CAFO risk. It is likely that there are strong differences between the demographic patterns of communities exposed to coastal flooding and those exposed riverine flooding, and because the delineation of this study area does not distinguish between these, it is possible that magnitude or significance of some correlations with flood risk are obscured. As such, the magnitude of correlations for environmental justice variables may naturally appear stronger for CAFO risk and weaker for flood risk. This has implications for the method of constructing variables representing natech risk and the interpretation of results when one constituent hazard explains a larger proportion of the variance in said variable than another constituent hazard.

### *6.2: Limitations*

The scope of this study is to be a descriptive assessment, rather than a predictive model for natech risk. Practical limitations affecting the scope of this research stem from the demarcation of the study area, the availability of detailed data on previous spills, and the lack of hydrological analysis. First, the study area for this research prioritized the inclusion of the maximum number of swine CAFOs while also seeking to avoid boundary issues that might arise when analyzing CAFOs or floodplains that exist on state borders. Maximizing the number data points came at the cost of introducing additional geographic and socioeconomic variation that likely influenced the strength of some of the correlations. Though this concern was mitigated by the choice to exclude urban centers that would have introduced high numbers of diverse CBGs that were distant from agricultural land, the study area still included some coastal communities whose markedly different incomes and demographics may have reduced the clarity of some of the environmental justice correlations.

Second, this study diverged from Carrel, Young, and Tate's (2016) in that the level of detailed documentation on CAFO discharge violations present in Iowa is not publicly accessible for the state of North Carolina. Data made available by the North Carolina Department of Environmental Quality is aggregated to the county level to protect the privacy of individual property owners. Without the XY coordinates and estimated volumes of previous events, making density surfaces or Poisson probabilities of spills must rely on approximations from the overlap of CAFO risk based on proxies and flood risk. As such, validating the findings of these analyses by comparing the patterns observed here with the distribution of historical swine waste natechs is not feasible. This limited the development of any sort of predictive application for this choice of study area. Without this data being easily accessible to researchers, the potential development and assessment of predictive models for natech risk in the North Carolina coastal plain is significantly impeded.

Finally, the introduction of hydrological analysis falls outside of the scope of this research. The inclusion of that expertise would, however, yield information that would be critical to providing detailed and actionable results to local policymakers. The volumes of additional data and expertise necessary for hydrological analysis of CAFO siting or more detailed flood risk assessment made such inclusions impractical for the scope of this study. Hydrological analysis would allow for the creation of risk assessments adjusted for the distance and total volume of available swine waste upstream of a given location, as well as the flow rate of the waterways in between. Future efforts to create predictive models for CAFO spills would greatly benefit from the consideration of hydrological context.

### *6.3: Future Research and Conclusion*

With climate change and the persisting concentration of swine CAFOs on North Carolina's coastal plain, waste spill natechs like those seen during Hurricanes Floyd and Florence are likely to become more of a threat in the future. These circumstances demand action to better protect vulnerable rural communities in the region, but many gaps still exist in our knowledge regarding the future of natech events and environmental justice. Despite the burgeoning growth of natech hazards research in the southeastern United States over the past two decades, the hazards research community still lacks methodologies for visualizing and assessing the implications of natech events on environmental justice, particularly in rural case studies. Though previous natech research has expressed concern about how the increasing complexity of the hazards is likely to adversely affect vulnerable communities, the research community does not yet have a strong foundation for quantifying or communicating those impacts. Better understanding how traditional environmental justice indicators are affected when environmental and technological risks are present simultaneously is a first step towards establishing a framework for assessing the socioeconomic impact of increasingly complex hazards landscapes.

Paths forward in better understanding the intersections of environmental justice include assessments of this relationship at different scales and with different industries. Conducting similar research using petroleum or chemical manufacturing facilities as the natech component will be a necessary step in confirming whether or not technological components of natechs generally explain more of the variance in natech risk. The hazard science community would also benefit from discussion over how best to combine component hazards in quantifications of natech risk and or further comparison of potential methods for combining variables into representations of natech risk.

This study yields useful considerations for local natech risk management and research. Because the statistically significant hotspots of the Natech Z proxy variable (which was shaped more by flood risk than its Natech X counterpart) were limited primarily to the primary and secondary tributaries, local decision making might benefit from further effort into further natech risk management and risk communication in the communities around these waterways. Additionally, though these findings did not always corroborate the findings of previous environmental justice assessments, they did indicate that certain communities are disproportionately situated in natech-prone areas, particularly those greater Hispanic/Latinx populations, lower incomes, and higher reporting of disabilities. Closer comparison of these results to those of previous studies may provide useful contributions in understanding how the demographics of exposed communities have changed over time.

These findings also reveal some important considerations for research into the implications of natech events for environmental justice research more broadly. The absence of emergent socioeconomic correlations appearing only when CAFO risk and flood risk were co-present is not entirely unsurprising, but the fact that the constituent hazards often had diverging correlations perhaps suggests a line of future inquiry for hazards researchers. If different types of hazards impact communities with different levels of homogeneity and may have diverging relationships with indicators of socioeconomic status, then understanding what happens to those indicators in the presence of both hazards might help refine understandings of environmental justice dynamics. Put another way, better understanding the differences between the environmental injustice that stems from natural hazards and the injustices that stem from anthropogenic hazards may help scholars and decisionmakers better respond to natech events in the future.

Because environmental justice is an inherently interdisciplinary concern, the insight of other fields will be needed to continue improving the linkages natech and environmental justice literatures. Input from social scientists, industrial engineers, and geophysical scientists will likely aid in the further refinement of strategies and best practices for assessing natech risk from constituent hazards. Because “natech hazards” encompasses a wide variety of potential threats, more studies like this one will be needed to develop a more complete picture of how environmental justice is shaped by the introduction of additional hazards. Because there is wide agreement in the natech literature that future disasters are likely to become more complex in the future, it is critical that the hazards research community keeps pace in ensuring that those methodologies are able to keep up with that growing complexity.

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# Appendix A: Additional Maps

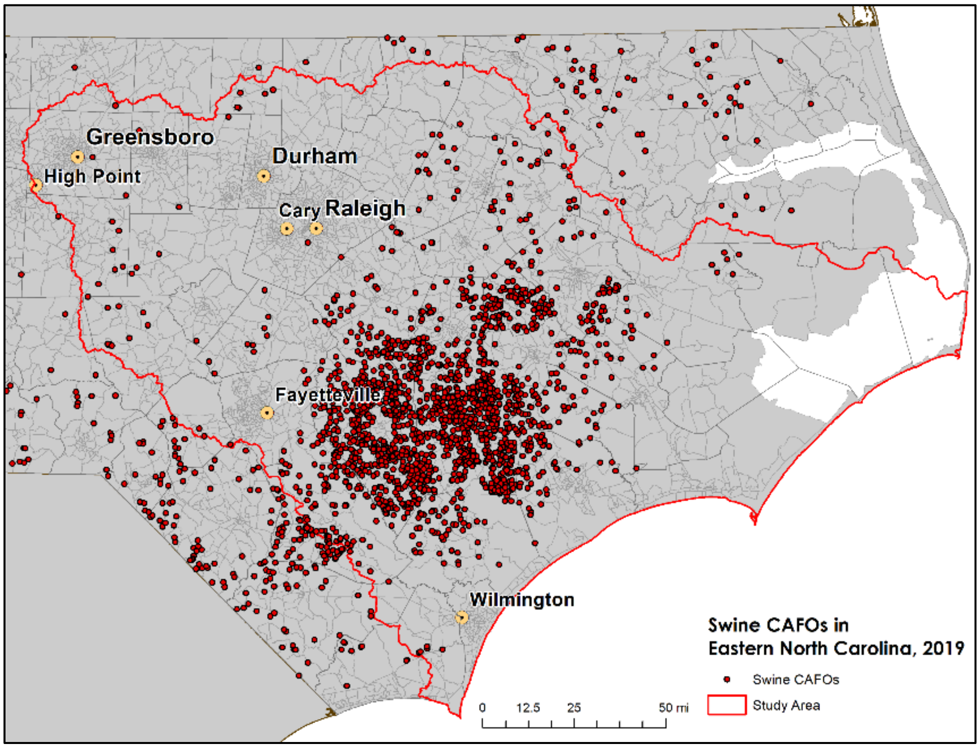


**Figure A.1:** Distribution of permitted swine CAFOs in eastern North Carolina as of February 2019

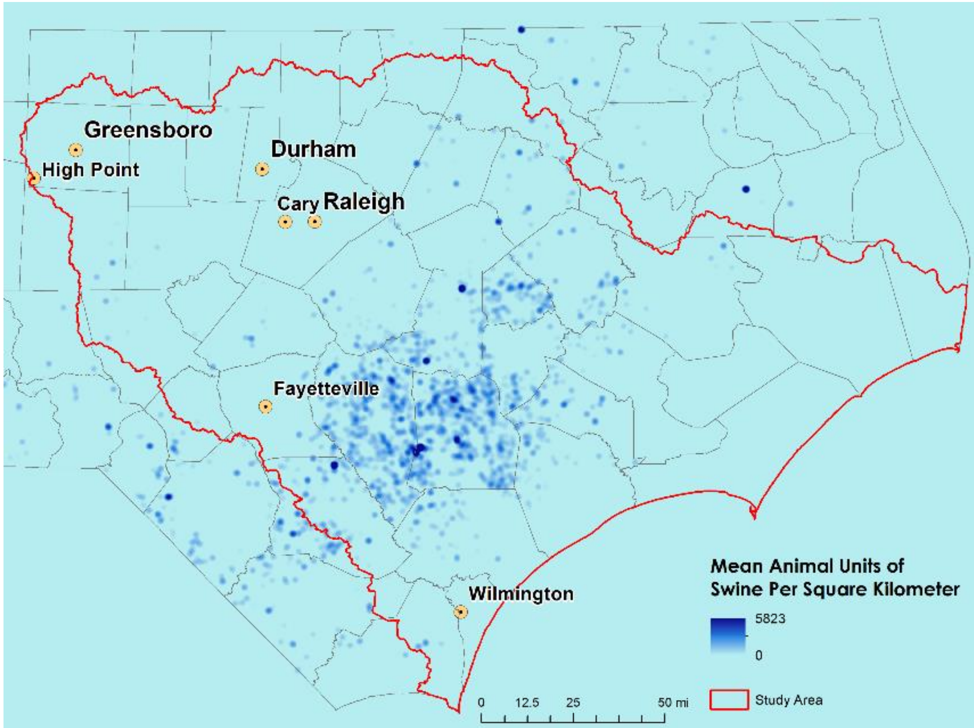


**Figure A.2:** Kernel density of swine AU per kilometer.