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A GIS-Based Risk Assessment for Fire Departments: Case Study of Richland County, SC

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A GIS-BASED RISK ASSESSMENT FOR FIRE DEPARTMENTS:
CASE STUDY OF RICHLAND COUNTY, SC

by

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ABSTRACT

Risk assessments enable fire departments to be better prepared for future incidents and to engage in more effective prevention activities. A combination of physical, demographic, and behavioral risk factors combined form a community's level of risk. This research shows how spatial and nonspatial statistical methods can be used within a GIS framework to create such a risk assessment, with the Columbia-Richland Fire Department in Richland County, SC being used as a case study. Hot spot analysis and thematic mapping of incident rates were used to assess the first research question – what is the spatial variability of structure fires, carbon monoxide incidents, and emergency medical calls? Correlation analysis, principal component analysis (PCA), and factor analysis were applied to a few dozen social and physical risk factors at the block group level to assess the second research question - how are the risk factors correlated with each other, and how are these risk factors varied across the county? The results of all types of methods were compared against each other to assess how risk factors correlated with incident types. These methods were able to map hot and cold spots of incidents, identify the most relevant risk factors, and show which risk factors were most prevalent in hot spot areas. The primary hot spot for EMS and fire incidents was found in northern Columbia, with a secondary hot spot located in far Lower Richland. PCA identified nine primary factors, the top three of which were related to systematic hard times, older homeowners, and rural location. Factor analysis was able to cluster block groups into fourteen groupings of similar risk traits. There were very clear differences in incident rates between the fourteen groupings, although hot spots contained block groups from multiple groupings. Given the snapshot in time nature of risk assessments, this research builds a baseline for future risk assessments, both in terms of methods and results.

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CHAPTER 1

INTRODUCTION

Hazards research primarily focuses on relatively rare events, such as natural hazards, major technological failures, or other large-scale human crises or disasters. In 2019 in the United States there were fourteen natural hazard events where overall damages reached or exceeded $1 billion, which combined resulted in 44 deaths (NOAA National Centers for Environmental Information (NCEI) 2020). Less frequently studied within the hazards field are the more common and smaller scale events such as structure fires, motor vehicle collisions, and medical emergencies, all of which occur daily almost everywhere in the country. In the United States from 2008-2017 each year had on average 46,700 structure fires, costing $10.6 billion in property loss, and resulting in 2,700 fatalities and 13,700 injuries (Federal Emergency Management Agency (FEMA) United States Fire Administration (USFA) 2019). These everyday events, frequently referred to as "incidents" or "calls", share similar response structures to the initial onset of larger hazard incidents. They both can also share similar risk factors and methods of assessing risk. Interestingly, the literature tends to stay relatively separate, with everyday structural fire risk discussed in journals like *Fire Safety Journal* or operations research journals, versus broader natural hazards-focused journals being at the core of hazards research.

Overall risk can be described as a combination of the physical hazard, social vulnerability, and people or items at risk (Cova 1999). In the case of structure fire risk, the physical hazard component can include variables such as the construction materials and design of the building, presence of sprinkler systems, proximity to vacant structures, availability of water for firefighting operations, and distance to the nearest fire station. In contrast, social vulnerability looks at the human component, considering how characteristics including age, gender, socioeconomic status, education, and languages spoken, impact a person or household's risk of suffering or dying in a fire. The occupancy of a building is important to consider because it determines the number of lives potentially threatened, the value of goods stored on the premises, their fuel load should they catch on fire, and if the activities occurring in the building pose a high potential for ignition (e.g., welding).

The fire service is traditionally thought of as just responding to fires, or as is said in the fire service, "putting the blue stuff on the red stuff," (i.e., putting the water on the fire). However, an increasingly large portion of emergency calls involve other types of incidents, such as medical calls, rescue incidents (motor vehicle crashes, water rescues, etc.), and unintentional carbon monoxide poisoning (CO) (Ahrens 2017). Unintentional CO poisoning can occur via improper use of generators indoors, or malfunctioning heating and cooking appliances, whereas intentional CO poisoning refers almost entirely to suicides. While specific risk factors for unintentional CO poisoning and certain types of emergency medical calls can vary, they still are a combination of multiple risk factors working in tandem. Mapping the location of specific physical, social, and potential occupancy components can therefore aid in assessing and visualizing the overall risk in an area.

Assessing these underlying levels of risk is an important activity for the fire service to plan effective response and prevention activities. Response planning includes the location of stations and specific apparatus (e.g., fire engine, ladder truck, etc.), whereas prevention activities might include inspections of commercial buildings, community outreach such as smoke detector installations, or fire safety educational programs at schools and senior centers. Knowledge of which types of risk are most important in a given community can help the fire service deliver the most appropriate and effective outreach (Higgins et al. 2013; Runefors, Johansson, and van Hees 2017; Singh Walia et al. 2018; Taylor et al. 2011). This has led to risk assessments being required as part of larger planning and accreditation processes for municipal fire departments (Amdahl 2001; Stouffer 2016). As part of their current work towards accreditation with the Center for Public Safety Excellence, the Columbia-Richland Fire Department (CRFD) is working on a risk assessment covering all of their response area throughout Richland County, South Carolina. This thesis provides part of that assessment.

This thesis focuses on two main ideas: the spatial variability of specific types of emergency response calls (i.e., "where"); and the correlation between each type of call and the underlying community variability in risk factors (i.e., "why"). More formally stated the research questions are as follows:

1. What is the spatial variability of structure fires, carbon monoxide incidents, and emergency medical calls in Richland County, SC?

2. How do underlying community variations in physical and social risk factors correlate with each other and with the types of emergency calls described in Research Question 1?

The incident types listed in Research Question 1 can be further broken down into seven different types; all incidents combined, all structure fires, structure fires resulting in civilian (as opposed to fire service) fatality, structure fires resulting in civilian injury, structure fires with no casualties (i.e., no fatalities or injuries), emergency medical calls, and carbon monoxide calls.

CHAPTER 2

LITERATURE REVIEW

2.1 Risk Assessment Methodology

Fire risk assessments are inherently spatial, as they consider the location of both the people and property at risk, as well as the fire department resources available for protection. As such, there is a long history of using spatial data to assess fire risk, first via paper maps, and then more recently using GIS and other computer-based spatial modeling tools. In the nineteenth and early twentieth centuries the insurance industry created detailed maps showing individual buildings labeled with details about the building construction and occupancy that influenced fire risk (Hensler 2011; Oswald 1997; Ristow 1981). The most well-known of these mapping firms was the Sanborn Map Company. The mid-twentieth century saw a shift in risk assessment from paper to computer-based methodology. Stronger building codes and improved fire protection systems made conflagrations where entire neighborhoods and cities went up in flames increasingly rare, which lessened the importance of collecting risk data for entire neighborhoods. At the same time computers allowed for more complex mathematical and statistical modeling based on actuarial and road network data (Tebeau 2003). In the last twenty years or so GIS has started to become more prevalent, adding explicit spatial location back into the risk models.

When considering the fire risk assessments of the mid-twentieth century to the present two clear methodological pathways emerge. First are the coverage assessments done to ensure equality in response times, where the goal is to minimize the response time (i.e., distance) of the nearest fire engine, defining risk as primarily based on distance to the nearest fire station. These assessments tend to use the road system and fire station location as the basis for mathematical network analysis. The initial modeling was more heavily mathematics-based (Flood 2010; Green and Kolesar 2004; Hogg 1968; Plane and Hendrick 1977; Toregas et al. 1971), whereas more recent iterations have been done within a GIS setting (Chevalier et al. 2012; Liu, Huang, and Chandramouli 2006; Murray 2013). Many of these studies take a very narrow perspective of fire risk, considering fire risk as purely a function of distance to the nearest fire engine. A few incorporate greater complexities into their modeling, such as weighting the model with qualitative risk data based on input from local fire officers (Çatay 2011; Plane and Hendrick 1977), including back-up coverage and second-due response vehicle placement (ReVelle 1991; Schreuder 1981), or other response time and operating cost variables (Badri, Mortagy, and Alsayed 1998; Park et al. 2016; Schilling et al. 1980).

The second pathway builds from a tradition of public health and medical GIS research, and maps the locations of incidents and their outcomes (fires, fire fatalities, etc.) against demographic and socioeconomic variables. Shai (2006) found a correlation at the census tract level between fire injury and low income, older (pre-1940) housing, vacant houses, and the ability to speak English in Philadelphia. Taylor et al. (2011) took fire risk information from previous public health studies about fire risk and used GIS to map socioeconomic-related risk for a UK fire service. In an applied variation, Higgins et al.

(2013) used GIS to build community profiles and a vulnerability assessment for the local fire service in Liverpool, UK. Corcoran, Higgs, and Higginson (2011) and Duncanson, Woodward, and Reid (2002) highlighted correlations between fire risk and socioeconomic deprivation by overlaying geocoded fire incidents on top of census-derived socioeconomic deprivation indices that had been previously developed by the wider public health community.

Harkening back to older assessments, like 19th century insurance agents working with Sanborn maps, some studies have considered building construction and other physical variables when assessing the variability in fire occurrence. Schachterle et al. (2012) examined the fire risk posed by proximity to vacant buildings in Baltimore using buffers around vacant buildings and broader building stock information at the census tract level. Barták et al. (2014) modeled the probability of building fire based on characteristics including structure age, building type, gas utilities, and presence of an elevator. A fire risk assessment done for Vientiane, Laos included building materials, flammable hazards (e.g., gasoline or propane storage), water supply, electrical wiring, building density, and history of past fires (Urban Research Institute 2004). Špatenková and Stein (2010) used not only building age, but also a number of human variables such as income, age, education, unemployment, and building occupancy.

At the same time that fire risk assessments were traversing their two pathways, there were significant conceptual and methodological developments in spatially based risk assessments within the larger hazards community. In the 1970's natural hazard researchers began to combine on-site surveying work similar to that done by Sanborn employees with computer-based mapping, statistical analysis, and remotely sensed data to identify flood plains, faults, avalanche paths, and landslides (Baker and McPhee 1975; Friedman 1975). Through the 1990's this research tended to focus on physical characteristics of the natural and built environment using a variety of raster, vector, and network models (Chou 1992; Lessing, Messina, and Fonner 1983; Shu-Quiang and Unwin 1992; Vega-Garcia, Woodard, and Lee 1993). In the 1990's and 2000's hazard risk assessments started to consider population, at first only considering the number of people (Emmi and Horton 1995; Sorensen, Carnes, and Rogers 1992), and then later on assessing more complex social vulnerability, often using census data (Cutter, Boruff, and Shirley 2003). In recent years a number of studies have used GIS to combine multiple physical and social vulnerability risk traits into comprehensive risk assessments (Boruff, Emrich, and Cutter 2005; Chakraborty, Tobin, and Montz 2005; Cutter, Mitchell, and Scott 2000; Ebert, Kerle, and Stein 2009; Szlafsztein and Sterr 2007; Tate, Cutter, and Berry 2010). Some of these focus on a single category of hazards, whereas others assess comprehensive risk to multiple types of hazards. In the fire service, multiple hazards might consist either of multiple types of fire risk (e.g., any fire vs. a fatal fire) or the many types of emergency calls that the fire service responses to (e.g., fire, medical, rescue, etc.).

Spatial and non-spatial statistical methods have been used in some fire and natural hazard risk and vulnerability assessments. Correlation analysis has been used to assess the strength of the relationship between fire incidents and risk variables (Barták et al. 2014). Factor analysis, including principal component analysis (PCA) has been used to reduce a large number of risk variables to a more concise set (Aksha et al. 2019; Boruff, Emrich, and Cutter 2005; Corcoran, Higgs, and Higginson 2011; Cutter, Boruff, and

Shirley 2003; Higgins et al. 2013; Lin 2004; Zhou et al. 2014). Cluster analysis has also been used to describe the epidemiology of fatal fires, including correlations in risk variables (Jonsson et al. 2017), and community profiles with shared fire risk patterns (Higgins et al. 2013).

2.2 Fire and CO Risk Factors

Fire and CO casualties (injuries and fatalities) are not found equally across all demographics (race, age, etc.) and are not spread equally across all communities (Corcoran, Higgs, and Higginson 2011; FEMA USFA 2018; Sircar et al. 2015). The majority of both types of calls occur at home, especially for fire fatalities (Ahrens 2017; Sircar et al. 2015). A number of demographic, behavioral, and physical built environment characteristics increase fire risk as highlighted in the literature.

2.2.1 Demographic Factors

Demographic variables include age, race and ethnicity, gender, and disability status. For example, the elderly have been found to have at least two to four times the average fire fatality risk, potentially due to higher rates of sensory and motor deficits which can impair one’s ability to detect and respond to a fire (FEMA USFA 2018; Holborn, Nolan, and Golt 2003; Jonsson et al. 2017; Warda, Tenenbein, and Moffatt 1999). Disability regardless of age has also been shown to increase ones fire fatality risk due to inability to recognize and/or properly react to fire risk (Holborn, Nolan, and Golt 2003; Lin 2004; Runyan et al. 1992; Warda, Tenenbein, and Moffatt 1999). Some researchers have also found a higher fire fatality risk in young children (Warda, Tenenbein, and Moffatt 1999), potentially due to needing assistance to escape a burning building, and curiosity around playing with fire (Shai and Lupinacci 2003), although more recent statistics show this risk appears to have diminished (FEMA USFA 2019). Racial and ethnic minorities, especially those with higher rates of poverty and in communities where English (or the main local language) is not the primary language have higher rates of fire and CO fatalities (Centers for Disease Control and Prevention (CDC) 1997; FEMA USFA 2018; Jennings 2013; Shai and Lupinacci 2003; Sircar et al. 2015). Men have higher fire fatality and injury risk, as well as higher CO fatality risk. This is likely due to behavioral risk factors such as being more likely to use fuel-burning tools and appliances (FEMA USFA 2018; Holborn, Nolan, and Golt 2003; Iqbal et al. 2012; Jonsson et al. 2017; Shai and Lupinacci 2003; Sircar et al. 2015).

2.2.2 Behavioral Factors

A number of other variables related to specific behaviors and other actionable characteristics have been associated with higher fire and/or CO risk. Some of these relate to an inability to understand prevention and warning information, whereas others relate to a higher risk of ignition. Overcrowding, unattended children, and smoking can all increase the chance of ignition, while alcohol impairment can encourage the likelihood of risky behavior or impair judgement in an emergency. Overcrowding can lead to an increased burden on the electrical system and other infrastructure within a building, as well as putting more people are at risk should a fire occur (Jennings 1999; Wallace 1990). Unattended children can lead to an increased fire risk because many small children are curious about fire and want to play with it, but do not yet understand the consequences of their actions (FEMA USFA 1997; Shai and Lupinacci 2003). Smoking (e.g., cigarettes, cigars, etc.) increases fire risk by increasing the chance of unintended ignition and increases fatality potential by ignition being very close to the potential victim (FEMA USFA 1997; Holborn, Nolan, and Golt 2003; Jennings 2013; Jonsson et al. 2017; Runyan et al. 1992; Xiong, Bruck, and Ball 2015). In contrast to the increased ignition risk posed by tobacco use, alcohol or drug use increases fire risk by influencing the likelihood of other risky behaviors (e.g., falling asleep while smoking, leaving food unattended on the stove) and by impairing one's ability to respond appropriately to an emergency scene (FEMA USFA 1997; Holborn, Nolan, and Golt 2003; Jonsson et al. 2017; Runyan et al. 1992; Turner et al. 2017; Xiong, Bruck, and Ball 2015).

2.2.3 Physical Building Characteristics

Another important piece of fire and CO risk is the building itself. Type of housing stock, condition of utilities, presence or absence of smoke and CO detectors, and building occupancy can all impact risk. Mobile homes and other substandard buildings have been found to have a higher fire risk, in particular in mobile home with limited exits (Runyan et al. 1992; Warda, Tenenbein, and Moffatt 1999). Jennings (1999) and Shai (2006) both note how inadequate long-term maintenance of a building leads to fire risk via things like older utilities (electrical, heating, etc.) not working properly, or buildings not being up to code in terms of egress or working smoke detectors. Wiring that is not able to handle the current electrical load, either due to age, poor installation, or overreliance on extension cords increases the risk of electrical fires (FEMA USFA 1997; Shai 2006; Shai and Lupinacci 2003; Urban Research Institute 2004). Improperly used space heaters can pose both a fire and CO risk (CDC 1997; FEMA USFA 1997; Hampson et al. 1994; Hampson and Stock 2006; Jennings 1999; Runyan et al. 1992; Sircar et al. 2015). The presence of functional smoke and CO detectors can go a long way in limiting fire and CO risk by notifying occupants of the problem before fire or CO levels become inescapable (FEMA USFA 1997; Jennings 1999; Runyan et al. 1992; Sircar et al. 2015). Owner occupied houses show lower fire and CO risk, likely because they have more incentives to protect the building as an asset, but also because owners have more control over building upkeep than rental tenants (FEMA USFA 1997; Shai 2006). Conversely, vacant buildings have higher fire risk than occupied buildings. They can be easy targets for arson, but they can also be the site of unintentional fires caused by squatters trying to keep warm or use electricity that had been previously cut off (FEMA USFA 1997; Jennings 1999; Shai 2006). Fires may also not be reported as quickly in vacant buildings.

2.2.4 Intersection of Demographic, Behavioral, and Building Traits

The combination of demographic, behavioral, and building traits associated with fire and unintentional CO poisoning risk paint a picture of risk correlated with low socioeconomic status. This is stated explicitly by many of the risk assessments for fire (Clark, Smith, and Conroy 2015; Corcoran, Higgs, and Higginson 2011; Duncanson, Woodward, and Reid 2002; FEMA USFA 1997; Jennings 1999) and CO (CDC 1997). Some of the factors relate directly to income or other wealth indicators, such as being able to afford home ownership and maintenance, rent in a well-maintained apartment building, adequate space for the number of people dwelling in a building, smoke/CO detector batteries, and/or daycare for small children. People with below a high school education were less likely to have a smoke detector installed and functioning, either due to not understanding the importance of smoke detectors and/or the strong correlation between low education and low income (Harvey et al. 1998). Low education and inability to speak the local language have been noted as risk factors for both fire (FEMA USFA1997; Harvey et al. 1998; Shai 2006) and CO (Hampson et al. 1994; Hampson and Stock 2006; Sircar et al. 2015) due to the communication issues they pose. This can be either directly by being unable to communicate with responders during emergency situations, or indirectly by reducing the likelihood that safety education messages will be understood and properly acted upon. Low education and inability to speak the local language can also exacerbate issues of low socioeconomic status by making it more likely one will have a low paying job or be unemployed. This gets at the broader issue of demographics and characteristics of low-income households and neighborhoods. For example, retirees living on a fixed income may not have the funds for building upkeep. A single parent working multiple low paying jobs is more likely to leave children without adult supervision due to lack of other options (Shai and Lupinacci 2003). Racial minorities have a long history of being under-valued by society as a whole, and thus underpaid and otherwise discriminated against. There can also be correlations between ignition risk factors and low socioeconomic status communities, such as a higher rate of tobacco usage among low income persons (Tobacco Free Kids 2015).

Knowing which parts of a fire department's response area has the highest call volume, or highest risk for specific types of calls, can be very helpful for planning and prevention purposes. Station, vehicle, and personnel placement can be determined by knowing where there is the greatest need (Amdahl 2001; Çatay 2011; Chevalier et al.

2012; Plane and Hendrick 1977; Urban Research Institute 2004). Research shows that if these kinds of planning decisions are made assuming all communities have equal risk, there can be tragic consequences. For example, large swaths of New York City burnt down in the 1970s after a number of stations were closed in high risk areas based on the results of shortsighted computer modeling (Flood 2010; Wallace 1990).

2.3 Emergency Medical Response and Community Composition

In addition to fire, CO, and rescue calls, many municipal fire departments also respond to some or all types of emergency medical calls. CRFD normally responds to the most critical types of medical incidents (cardiac arrest, unconscious patient, major trauma, etc.) and to less serious incidents when the ambulance has a delayed response time. Richland County Emergency Medical Services (Richland County EMS) provides all emergency ambulance services for the county and responds to all emergency medical calls, whether or not CRFD responds.

Starting rapid medical care, including efforts by first responders prior to hospital arrival or even ambulance arrival can make a difference in survival and outcome in the most severe medical incidents (Blackwell and Kaufman 2002; Malta Hansen et al. 2015). First responder training includes skills like CPR, defibrillation, and basic first aid such as controlling bleeding (Le Baudour, Bergeron, and Wesley 2019; United States Department of Transportation, National Highway Traffic Safety Administration 2009). Much of the research on rapid emergency medical care has looked at early CPR and defibrillation for cardiac arrest victims (Malta Hansen et al. 2015; Shuster and Keller 1993; Smith, Peeters, and McNeil 2001; Vaillancourt, Stiell, and Canadian Cardiovascular Outcomes Research

Team 2004). Research on rapid transport of trauma calls has had more contradictory results (Rogers, Rittenhouse, and Gross 2015), with some works showing rapid transport of patients improves survival time (Swaroop et al. 2013), and other works showing no difference in survival (Newgard et al. 2010; Pons and Markovchick 2002), suggesting that a number of factors are at play for trauma mortality. Timely prehospital interventions have been shown to reduce mortality for a few specific types of trauma and medical incidents, such as tourniquet use for arterial bleeding of a limb (King, Larentzakis, and Ramly 2015; Kue et al. 2015; Scerbo et al. 2017) and use of naloxone for opioid overdoses (Davis et al. 2014; Weaver, Palombi, and Bastianelli 2018). The time difference between first responder and ambulance arrival has been shown to be less important for lower acuity calls (Cone, Galante, and MacMillan 2008). Inclusion of first responders, including firefighters, police, and other trained community members in the medical emergency response system has been shown to provide a faster response than when only using ambulances, thus providing the opportunity to start patient care sooner (Gee 2007; Kellermann et al. 1993; Malta Hansen et al. 2015; Shuster and Keller 1993; Smith, Peeters, and McNeil 2001).

Ambulance usage has been found to vary with age, poverty, insurance status, and urban versus rural location all affecting the likelihood of arriving at a hospital via ambulance. Studies have found that the elderly are more likely to be transported by ambulance (Rucker et al. 1997; Squire, Tamayo, and Tamayo-Sarver 2010; Svenson 2000; Young et al. 2003). This is in part due to a general increase in health problems with age, but in some cases also related to having fewer alternative options for transportation, such as a widow(er) no longer having a spouse who could drive them to the emergency room. Socioeconomic variables such as income and insurance status have also been found to be unequally distributed among ambulance users, with patients with lower income and those who were uninsured or with public health insurance (Medicare, Medicaid) more likely to use an ambulance to reach treatment (Meisel et al. 2011; Rucker et al. 1997; Squire, Tamayo, and Tamayo-Sarver 2010; Svenson 2000). Young et al. (2003) and Meisel et al. (2011) have also noted how urban versus rural location can impact whether an ambulance or private transportation is taken to the hospital.

2.4 Summary

The relevant literature can be divided into three overarching themes, risk assessment methodology, previously identified risk factors, and the role of emergency medicine (i.e., EMS) within the fire service. Risk assessments have progressed chronologically from highly detailed paper insurance maps in the 19^{th} and early 20^{th} century, through network analysis of the mid-20^{th} century quantitative revolution and public health focused summaries of fire victim traits, to comprehensive assessments combining physical and social risk factors. Many of the later assessments are GIS-based, and there have been huge advancements made in this area by the larger hazards community. The fire risk assessment community is starting to embrace GIS and comprehensive assessments, but risk assessments based purely on physical infrastructure are still common.

Previously identified risk factors can be broken down into a number of key areas, starting with fire, CO, and EMS risk factors, and then moving into the additional detail of demographic, behavioral, and physical risk factors as well as the intersection between all three. Demographic variables include age, race and ethnicity, gender, and disability status. Men, racial and ethnic minorities, the elderly, and the disabled all have a higher risk of fire or CO fatalities. Behavioral risk factors, such as overcrowding or unattended children can contribute to an inability to understand prevention and warning information, whereas other behavioral risk factors like alcohol and tobacco use contribute to a higher risk of ignition and improper response in an emergency. Low education and inability to speak the local language can also pose a higher fire and CO risk due to inability to understand prevention and warning information, as well as increasing the likelihood of other risk factors related to low income. Physical risk factors, such as the type of housing stock, condition of utilities, presence or absence of smoke and CO detectors, and building occupancy can all impact risk. Mobile homes and substandard or poorly maintained buildings are at higher fire risk, as are those that lack working smoke and CO detectors and those that are vacant. The combination of demographic, behavioral, and building traits associated with fire and unintentional CO poisoning risk paint a picture of risk correlated with low socioeconomic status, which has been explicitly stated in multiple assessments.

The role of the fire service within the emergency medical response community varies by department, with some fire departments being the primary ambulance provider and other departments (including CRFD) only responding to a portion of the most serious types of medical incidents. Starting medical care in a prehospital or even pre-ambulance setting has been shown to be highly beneficial and time sensitive for some types of acute calls (e.g., cardiac arrest, severe bleeding from an extremity, opioid overdose), although less time sensitive for emergency medical incidents as a whole. Studies have found that ambulance usage is unevenly distributed across the population, with the elderly, the impoverished, and those with no insurance or only public insurance being more likely to request an ambulance.

CHAPTER 3

DATA AND METHODS

3.1 Study Area

The study area covers CRFD's response territory, which consists of all of Richland County minus the town of Irmo and the local military installations. Richland County covers 757 square miles, with a population of approximately 415,000 as of 2018 (United States Census Bureau 2018). At the center of the county lies the city of Columbia, which serves as the state capitol. The center of the county around Columbia is urbanized, with population density decreasing towards the outer edges of the county through suburban and rural areas. The city of Columbia averages 978 people per square mile, whereas the rest of the county averages only 450 people per square mile. As of 2018, 48.2% of the county identifies as African-American, 45.9% as white, 2.9% as Asian, 2.4% as mixed race, and less than 0.5% as Native American or Native Hawaiian/Pacific Islander. Overall 5.2% of the population also identifies as Hispanic. Minors under age 18 comprise 21.4% of the population, and 12.7% of the county is over age 65 (United States Census Bureau 2018).

Fire service in Columbia began in 1802, with a number of white and African-American volunteer companies serving the city until the establishment of CRFD as a career department in 1903 (Jansen 2005). African-American firefighters either served in all roles in segregated volunteer companies, or as drivers for primarily white companies. The first fulltime African-American firefighters were hired in 1953 (Hart 2000). CRFD took over fire operations for most of the county in 1985, absorbing the existing volunteer fire departments (*The Columbia Record* 1985). The one holdout volunteer department, the Capital View Fire District, continued to exist as a separate entity until the early 2000's when it too was absorbed by CRFD. The remaining exceptions are Fort Jackson, McCrady Training Center, and McEntire Joint National Guard Base, which as military installations operate their own fire departments. In addition, the town of Irmo also operates its own fire district which spans parts of Richland and Lexington Counties. Currently CRFD relies on 491 career staff and 120 volunteers to staff thirty-two fire stations spread across all of Richland County (Figure 3.1). The stations within Columbia city limits are staffed entirely by career personnel, whereas the stations in the rest of the county are manned by both career and volunteer firefighters. All but one station has a fire engine, and six stations have ladder trucks. Some stations also host vehicles such as rescue trucks, brush trucks, and tankers. CRFD is organized geographically into five battalions. Battalion 1 covers the center of Columbia, Battalion 2 covers the portion of CRFD's response area on the western side of the Congaree and some of north Columbia, Battalions 3 and 5 split the rest of the north end of Richland County, and Battalion 4 covers all of Lower Richland County (Columbia-Richland Fire Department 2019).

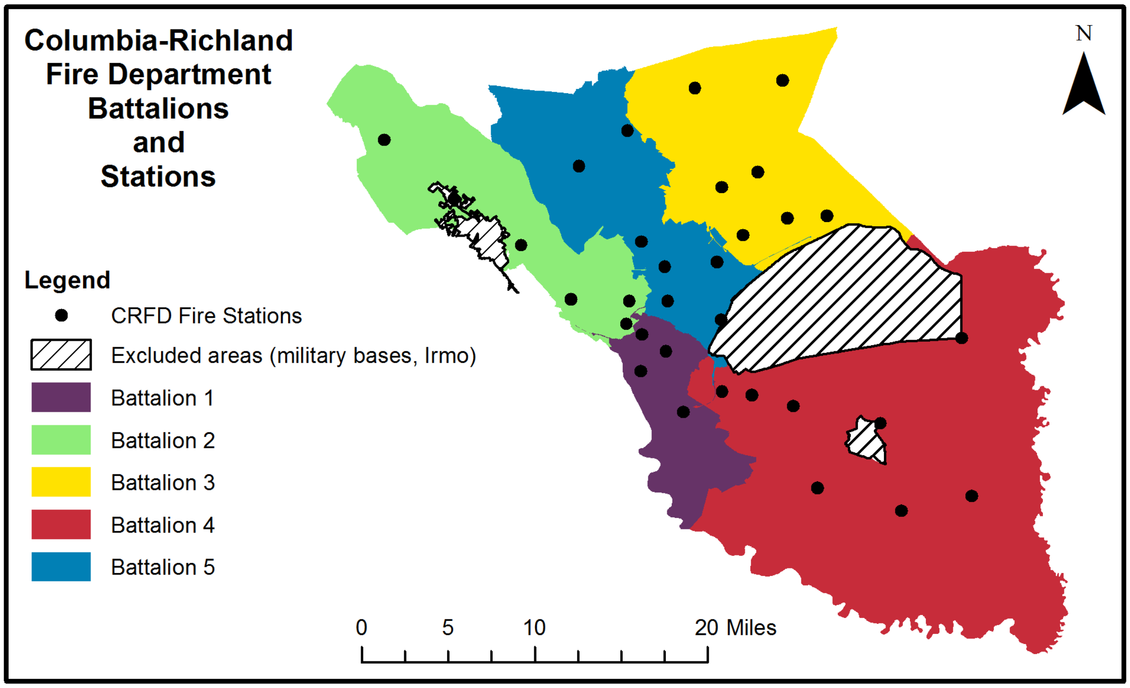

Figure 3.1: Map of Columbia-Richland Fire Department territory including battalion boundaries and station locations

3.2 Data

Many different types of physical and social risk variables related to fire and CO risk and EMS usage are available in GIS format. Table 3.1 lists datasets of risk variables identified in the literature, as well additional supporting datasets such as road networks and population. Spatial and temporal scale and update frequency vary depending on the dataset, with the most recent edition used in analysis. For consistency, all layers were re-projected to Universal Transverse Mercator (UTM) Zone 17N (NAD 83 datum). In addition, the boundaries of Irmo and the military installations available from the US Census (2019 TigerLine datasets) were used to mask out areas of Richland County that CRFD does not respond to. Census demographic and socioeconomic data is available at the block level from the 2010 Census, and at as five-year estimates down to the block group level from the US Census American Community Survey (US Census ACS). This work primarily used the most recent US Census ACS estimates (2013-2017) at the block group level, with population data at the block level from the 2010 Census used in preprocessing to identify non-populated areas. Analysis of Census data was at the block group level as statistical analysis showed that block groups had a smaller margin of error than the census tracts. For further details, see Appendix A.

Table 3.1: Input GIS-based datasets

Risk Variable	Dataset Source	Date	Variable Measurement(s)
Fire engine location	South Carolina Geographic Information Systems (SC GIS) layer with CRFD attribute additions	2019	Average distance to engine
Ladder truck location	SC GIS layer with CRFD attribute additions	2019	Average distance to ladder truck
Tanker truck location	SC GIS layer with CRFD attribute additions	2019	Combined with hydrants – average distance to water supply
Hydrant locations	CRFD Hydrants	2019	Combined with tanker trucks – average distance to water supply
Road Network	South Carolina Department of Transportation (SCDOT) Statewide Highways and Statewide Other Roads	2019	Used in preprocessing
Rail Network	SCDOT Statewide Railroads	2019	Average number of grade crossings
Populated areas	US Decennial Census	2010	Used in preprocessing
Age	US Census ACS	2013-2017 estimates	Under 18, 18 to 50, over 50 (thresholds tested in PCA)
Race/Ethnicity	US Census ACS	2013-2017 estimates	White, Black, Asian/Pacific Islander,

			Native American, Other/Two+ races, Hispanic
Gender	US Census ACS	2013-2017 estimates	Male, Female
Poverty	US Census ACS	2013-2017 estimates	% households below poverty in last 12 months
Education levels	US Census ACS	2013-2017 estimates	No high school diploma/GED (threshold tested in PCA)
Home ownership	US Census ACS	2013-2017 estimates	% owner occupied home
Vacant housing	US Census ACS	2013-2017 estimates	% vacant
English language ability	US Census ACS	2013-2017 estimates	% English not spoken well
Overcrowded housing	US Census ACS	2013-2017 estimates	% with >1 occupant per room
Children with limited supervision	US Census ACS	2013-2017 estimates	% households with children headed by a single adult
Health insurance status	US Census ACS	2013-2017 estimates	No insurance, only Medicaid/Medicare
Disability status	US Census ACS	2013-2017 estimates	% households with 1+ disabled persons
Building Age	US Census ACS	2013-2017 estimates	Old (pre-1940), Post War (1940-1979), Late 20th Century (1980-1999), Early 21st Century (2000-present)*
Housing Type	US Census ACS	2013-2017 estimates	One/Two Family, Multi Family, Mobile Home, Vehicle as home
Alcohol abuse	Alcohol sales data (Esri Business Analyst)	2019	Total alcohol sales (measurement tested in PCA)
Smoking	Smoking product sales data (Esri Business Analyst)	2019	Total smoking product sales (measurement tested in PCA)

** These housing age breaks were determined based off of eras of housing construction methods and transition to mandatory building codes statewide (U.S. Department of Housing and Urban Development 2001; South Carolina Building Codes Council 2019).*

CRFD incidents relating to fires, CO incidents, and emergency medical services from 2012 through 2018 have been gathered from the National Fire Incident Reporting System (NFIRS). These were the types of incidents CRFD administration requested be assessed, not the complete set of all CRFD incidents, which would have included calls like faulty alarms, hazardous material incidents, and rescue incidents. The NFIRS dataset, based on incident reports written up after every single call, is the most complete record of past incidents that has been collected. Each incident report includes the street address, which was geocoded with the Esri World Geocoder to enable its use with the other GIS layers. Incident reports also include information on whether any injuries or fatalities of citizens or firefighters occurred. The types of calls included in the analysis are those categorized by NFIRS codes for fire in structures (110s and 120s), CO incidents (414), and medical responses (311 and 321). Incidents outside the study area where mutual aid was provided to neighboring communities were excluded. Incidents on interstate highways or otherwise unable to be precisely geocoded were also excluded from the final analysis. This left a total of 69,772 incidents, of which 3,800 were fire incidents, 121 were CO incidents, and 65,851 were medical incidents (Table 3.2).

Table 3.2: Incident and battalion overview

	Battalion 1	Battalion 2	Battalion 3	Battalion 4	Battalion 5	Total
All Incidents (EMS, CO, Fire)	6,716	18,692	14,147	12,013	18,204	69,772
EMS	6,146	17,659	13,355	11,397	17,294	65,851
CO	21	22	31	14	33	121
All Structure Fires	549	1,011	761	602	877	3,800
- Incidents with injuries	13	20	11	10	22	76
- Civilian injuries	16	27	12	11	23	89
- Incidents with fatalities	4	3	0	4	10	21
- Civilian fatalities	4	3	0	4	11	22
- No Casualties	532	988	750	589	845	3,704
Population	58,634	97,239	110,679	51,700	70,059	388,311
Area (Sq. Miles)	47.69	100.58	124.21	308.68	102.18	683
Number of Fire Stations	4	6	7	8	7	32

3.3 Data Preprocessing

Methods can be divided into multiple preprocessing steps and the main geospatial and statistical analysis, a graphical overview of which can be seen in Figure 3.2. Some preprocessing of data was required to convert the datasets shown in Table 3.1 into the appropriate format for statistical processing. The main areas of preprocessing involved the Census data, military boundaries, fire station apparatus, and railroad grade crossings. GIS-based preprocessing was done using ArcGIS, with some of the Census calculations being done in Excel. Explicit details about input parameters and processing steps are in Appendix B.

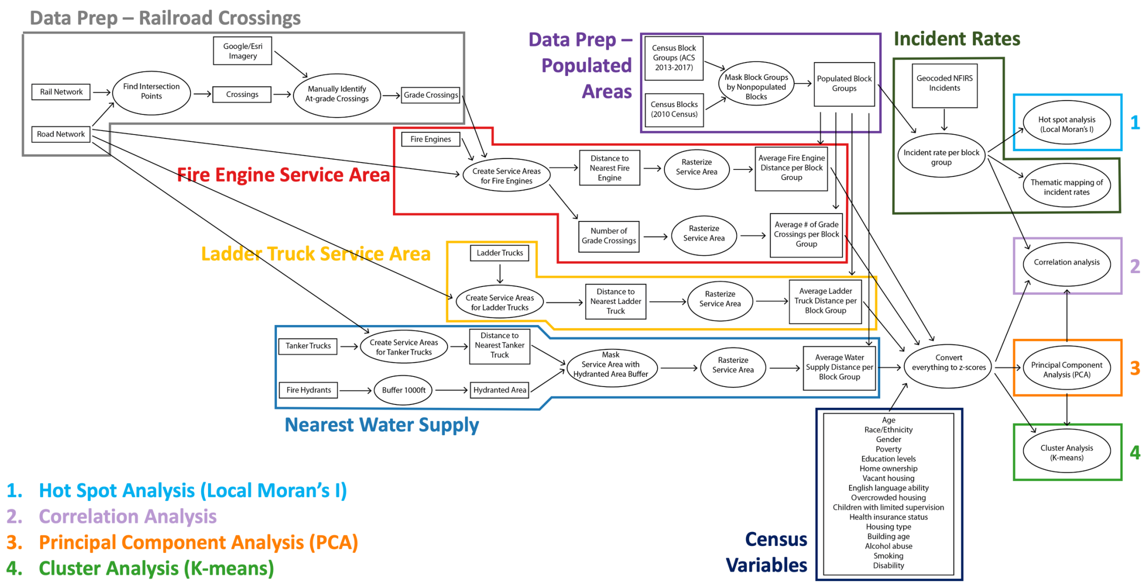

Figure 3.2: Methodology overview

Census data preprocessing involved two main pieces. First, Excel was used to convert the more general risk variables listed in Table 3.1 into the specific risk variables shown in Table 3.3. This included combining columns as well as calculating percentages rather than strict counts. Some of these risk variable measurements are based on the number of people (i.e., per capita), whereas others are based on the number of households or housing units. Some block groups had people, but no households or housing units (e.g., students living in college dorms), resulting in divide by zero errors for the variables based on households or housing units. These values were manually set to zero, reflecting that none of that block group had the trait in question. See Appendix C for full details.

Second, 2010 Census blocks were used to spatially apportion population across the ACS block groups given that ACS data is not available at finer than block group resolution. Instead of assuming that the population of a block group is equally distributed across the entire area, block level data was used as a mask so that population was spread across only those blocks with at least one person or household. This removes unpopulated areas like parks and lakes from calculations like assessing distance to the nearest apparatus. As an example, see Figure 3.3, where a block group containing a park (green rectangle), lake (blue oval), and college dorm (gold square) is divided into twelve blocks. Section (a) shows the population in terms of people and households, section (b) shows an even distribution of people where one dot represents ten people, and section (c) shows the same population redistributed. In the redistributed section there are no longer any people in the blocks covering the park and western side of the lake. The eastern side of the lake, with newly built houses (i.e., households) but no people, and the college dorm, with people but no households, both remain populated. While this method does not perfectly apportion people to populated areas, it creates a closer approximation than equally distributing people across an entire block group.

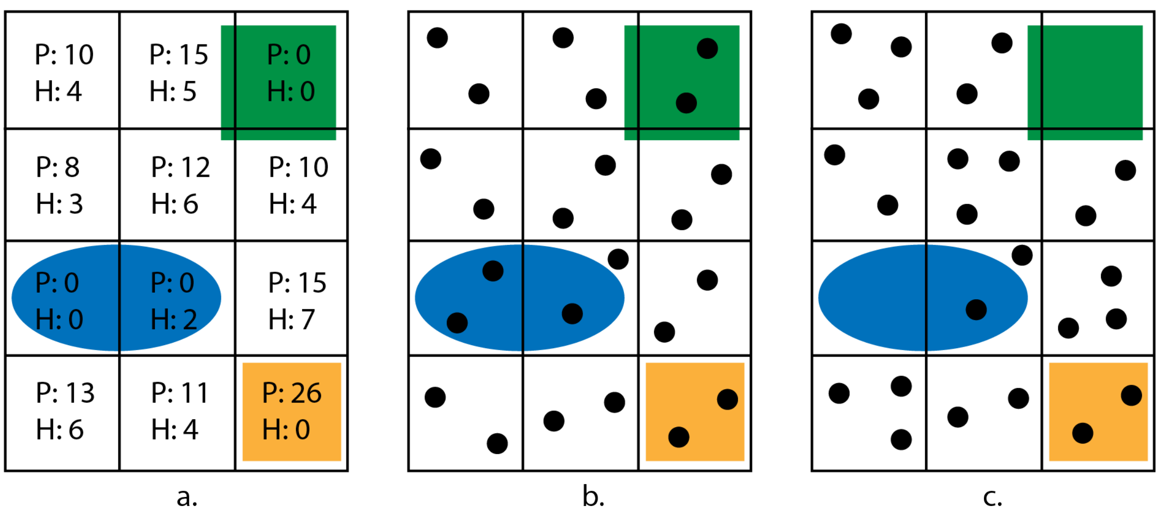

Figure 3.3: Population apportioning example.
This figure shows how block population is used to distribute people around the block group. The subsections show (a) the population in terms of people and households, (b) an even distribution of people where one dot represents ten people, and (c) the same population redistributed according to the method described above.

Richland County military boundaries – Fort Jackson, including McCrady Training Center, and McEntire Joint National Guard Base – were identified from the military boundary layer available from the US Census Bureau. In some places, the property line was identical to the neighboring road network, so in order to not exclude these roads from network analysis calculations the military base boundaries were buffered inwards by one hundred feet. This layer was used both as a polygon barrier during the service area analysis, since civilian vehicles are unable to easily drive through these properties, as well as a mask when defining the CRFD response area.

Calculation of average distance to fire engine, ladder truck, and water supply involved the creation of service areas using the ArcGIS Network Analyst toolbox. To approximate a surface showing the continuous distance away from the nearest fire apparatus via the road network, network analysis service areas were calculated in small increments and then rasterized. A threshold of 0.1 miles was used to build rings around each apparatus under consideration (fire engines, ladder trucks, and tankers), building out along the road networks to either the county boundary or the point at which a location was closer to a neighboring fire station. Each ring was assigned the value of the inner boundary, such that the 0.1 to 0.2 mile ring would be labeled as 0.1 miles. The rings were then rasterized with a pixel size of 15 meters, which corresponds with the standard fifty-foot fire hose section length. At this point for fire engines and ladder trucks the populated block group boundaries were used with the distance rasters to calculate average distance to the nearest apparatus per block group. To calculate the distance to the nearest water supply the distance to the nearest tanker raster was first masked by the hydranted area layer (i.e., hydrants buffered by 1000 feet), with hydranted areas being considered to have zero distance to the nearest water supply. Then like the engines and ladder trucks the populated block group boundaries were used to calculate the average water supply distance per block group.

Railroad at-grade-level crossings (aka grade crossings) had to first be identified, and then the fire engine service areas had to be segmented to show which areas require the nearest fire engine to cross one or more grade crossings. Railroad grade crossings were identified by intersecting railroad and street networks, and then using underlying imagery (Esri, Google Earth, etc.) to identify whether the crossing is above, at, or below grade (street level). The majority of railroad crossings in Richland County are at grade level, necessitating vehicle traffic stop when a train is going through the crossing. While the US Department of Transportation Bureau of Transportation Statistics does have a publicly available railroad crossings GIS layer, a quick comparison of it with underlying imagery showed that it was several years out of date, including crossings on rail lines that have since been removed as well as missing other existing crossings.

Identifying the number of grade crossings between a location and the nearest fire engine involved calculating overall service areas to determine the closest fire engine, and then manually dividing the service area into sections based on the attribute of how many grade crossings were between the region and the nearest fire station. An area that had a grade crossing on the shortest route from the fire station, but also had a slightly longer route with no grade crossings was not considered blocked by a grade crossing. This recognized that if a train is blocking the tracks emergency response vehicles will detour on a longer route if necessary, instead of being completely halted by a train in order to reach an emergency incident. Most areas had zero or one crossings between them and the nearest engine, with a few areas having two crossings in the way. No areas had more than two grade crossings between them and the nearest fire engine.

3.4 Data Reduction

A large number of physical and social risk factors (Table 3.3) were considered as part of Research Question 2, which assesses how these risk factors are correlated with each other and with the different types of emergency incidents under consideration. Factor analysis, specifically PCA run in SPSS, was used to reduce this large number of risk variables into a smaller number of related factors for use in other parts of the analysis. There was some initial uncertainty about the most appropriate age thresholds and measurements of four variables – under education, age, alcohol use, and tobacco use. The variations on these four variables were as follows: under education defined as either below an 8th grade education or only a high school diploma/GED; alcohol and smoking usage (two separate variables) defined using either total sales data or household average; age broken into three categories (children, adult, elderly) at either age 5 or 18 (child-adult threshold) and at age 50 or 70 (adult-elderly threshold). Instead of arbitrarily choosing from these options, sixteen PCA trials were run in order to identify which age thresholds and measurements resulted in the greatest explained variance. The other twenty-seven variables remained constant throughout all sixteen trials. In order to have consistency in units and data ranges, measurements of all risk variables were converted to z-scores prior to use in PCA (Table 3.3). The principal components developed by the trial with the greatest explained variance were used in all further analysis involving PCA output. For further details of PCA processing, see Appendix B.

Table 3.3: Table of risk variables used in PCA.

Variable Name	Variable Description*
Fire Engine Distance	**Average distance to nearest fire engine**
Ladder Truck Distance	**Average distance to nearest ladder truck**
Water Supply Distance	**Average distance to nearest water supply**
Railroad Grade Crossings	**Average number of grade crossings to nearest engine**
Alcohol	**Total dollars spent on alcohol** OR Average spending on alcohol per household
Smoking	**Total dollars spent on smoking products** OR Average spending on smoking products per household
Owner Occupied	**Percent of occupied housing owner occupied**
Vacant	**Percent of vacant housing**
Crowded	**Percent of occupied housing with 1+ people per room (crowded)**
Under Education	Below 8^{th} grade education OR **Below high school diploma/GED**
Unattended children	**Percent of kids living in a household by a single adult**
Poverty	**Percent of households below poverty in the last 12 months**
Age	Percent: Under 5 years, 5 to 49 years, 50 years or older OR **Under 18 years, 18 to 49 years, 50 years or older** OR Under 5 years, 5 to 69 years, 70 years or older OR Under 18 years, 18 to 69 years, 70 years or older
Race: White	**Percent of population identifying as White/Caucasian**
Race: Black	**Percent of population identifying as Black/African-American**
Race: Asian	**Percent of population identifying as Asian/Pacific Islander**
Race: Native American	**Percent of population identifying as Native American**
Race: Other/Two or more	**Percent of population identifying as other race or of two or more races**
Ethnicity: Hispanic	**Percent of population identifying as Hispanic**
Housing Type: One or Two Family	**Percent of housing units that are one- or two-family homes**
Housing Type: Multi Family	**Percent of housing units with three or more units within one building**

Housing Type: Mobile Home	**Percent of housing units that are mobile homes**
Housing Type: Vehicles	**Percent of housing units that are vehicles being used as homes**
Insurance: None	**Percent of population with no medical insurance**
Insurance: Medi Only	**Percent of population with only Medicare and/or Medicaid**
Poor English	**Percent of households with limited English-speaking ability**
Housing Age: Old	**Percent of housing units built in 1939 or before**
Housing Age: Postwar	**Percent of housing units built from 1940 to 1979**
Housing Age: Late 20th Century	**Percent of housing units built from 1980 to 1999**
Housing Age: Early 21st Century	**Percent of housing units built from 2000 to the present**
Disability	**Percent of households with at least one disabled person**

*Bolded options are those used in best PCA output.

3.5 Statistical Analysis

Statistical analysis consisted of hot spot analysis, correlation analysis, and cluster analysis. Hot spot analysis was used to address Research Question 1, the spatial variability of the different types of incidents. Thematic mapping of incident results was used to check the consistency of the hot spot analysis results. Correlation analysis and cluster analysis were used in combination with the aforementioned factor analysis output to address Research Question 2, the variations in physical and social risk factors between communities and their correlation with the different types of emergency incidents.

The number of overall incidents was too large for patterns to be clearly distinguishable by mapping individual incidents as points. Incidents were spatially grouped in two ways; by mapping incidents at the block group level, and by using hot spot analysis, specifically Local Moran’s I. Local Moran’s I identifies spatially adjacent sets of statistically significant high or low values (i.e., hot or cold spots), as well as identifying outliers of either extreme (Anselin 1995). Both of these methods were run on each of the seven incident types using ArcGIS. In order to account for population differences between block groups, incident rates were used instead of raw incident numbers. For the specific input parameters used with Local Moran's I see Appendix B.

Correlation analysis was run between each of the seven different types of incidents and each of the risk variables to determine which risk variables showed a significant correlation with each type of incident. A second set of correlation analysis was run to compare the PCA output factors with the seven different types of incidents as another way to assess which factors aligned most strongly with individual types of calls. Significance of r-values was determined via hypothesis testing using a t-test.

Cluster analysis, specifically K-means, was run in ArcGIS to assess which block groups have similar risk profiles. K-means was run on both the original input variables (converted to z-scores) recommended by the PCA run with greatest explained variance, as well as on the nine principal factors produced by that PCA run. In both cases the input parameter to evaluate the best number of groupings was used. For further details on input parameters see Appendix B. The PCA-based K-means output was found to be the more useful of the two K-means trials and thus was used in additional comparisons with other processing results.

3.6 Methods Summary

The methodology began with GIS-based data preprocessing to convert raw datasets into clean risk variable measurements useable in further spatial and non-spatial statistical analysis. Next factor analysis, specifically PCA, was used to reduce a large set of risk variables into a more manageable set of principal factors. Hot spot analysis was used to answer Research Question 1 (the “where” question). Research Question 2 (the “why” question) was answered by a combination of the factor analysis with correlation analysis and cluster analysis. These methods allowed for consideration of incident hot and cold spots, correlation between risk variables and incident types, and shared patterns between risk variables. Similar risk profiles across multiple block groups were identified, as were the most impactful risk variables for each block group.

CHAPTER 4

RESULTS

Research Question 1, the spatial variability of the different types of incidents (i.e., all incidents combined, EMS, CO, all structure fires, and structure fires grouped by those with fatalities, injuries, or no casualties) was answered using Local Moran's I and thematic mapping of incident rates. Due to EMS incidents comprising a significant percentage of total incidents, these incident types tended to increase or decrease in concert and show nearly identical spatial patterns. A similar dynamic was observed in the number of no casualty fire incidents moving in tandem with total fire incidents. Research Question 2 considers how underlying community variations in physical and social risk factors correlate with each other and with the different types of incidents. It was addressed using a combination of PCA, correlation analysis, and K-means analysis. PCA was used to reduce a large number of risk variables into a smaller set of related factors, which were then used in correlation analysis and K-means. Correlation analysis identified which risk factors were correlated with each type of incident, and K-means was used to cluster block groups with similar patterns of risk factors.

4.1 Incident Distribution

The first research question examines the spatial variability of each type of incident across Richland County. The number of incidents was generally too large for patterns to be clearly distinguishable if mapping individual incidents as points, thus the annual incident rate per 10,000 people was calculated for each block group. Local Moran's I was used to identify hot/cold spots of block groups and outlier block groups. Thematic mapping of incident rates was also used as a way to check for consistency with the Local Moran's I results. Incidents were not distributed evenly across the county using either methods.

4.1.1 Hot Spot Analysis

Local Moran's I identified which block groups have statistically significant high or low values compared to their neighbors. This can be either as a group of neighboring extreme values (i.e., hot or cold spot) or as a lone outlier. Hot spots are termed "high-high" or high values surrounded by other high values, with cold spots correspondingly named "low-low". A high outlier surrounded by low values is referred to as "high-low" and a low outlier surrounded by high values as "low-high". All types of incidents showed hot and cold spots as well as both high and low outliers in the Local Moran's I results. There was significant variation in which block groups were the outliers or within hot/cold spots depending on the type of incident.

The four types of incidents with a large number of calls (all calls, EMS, all fire, fire no casualties) had geographically larger hot and cold spots with a few high and low outliers. They all had hot spots in northern Columbia. Overall calls and EMS incidents had a secondary (smaller) hot spot in Lower Richland, a primary cold spot around central Columbia, and a secondary cold spot north of Irmo (Figure 4.1). All fire calls and no casualty fire calls had their main cold spot to the north and west of Irmo, with a small secondary cold spot in the Rosewood neighborhood (Figure 4.2). Outliers were mainly found near the opposite type of hot or cold spot (e.g., a low outlier next to a hot spot), with the exception being one or two block groups in northeastern Richland County.

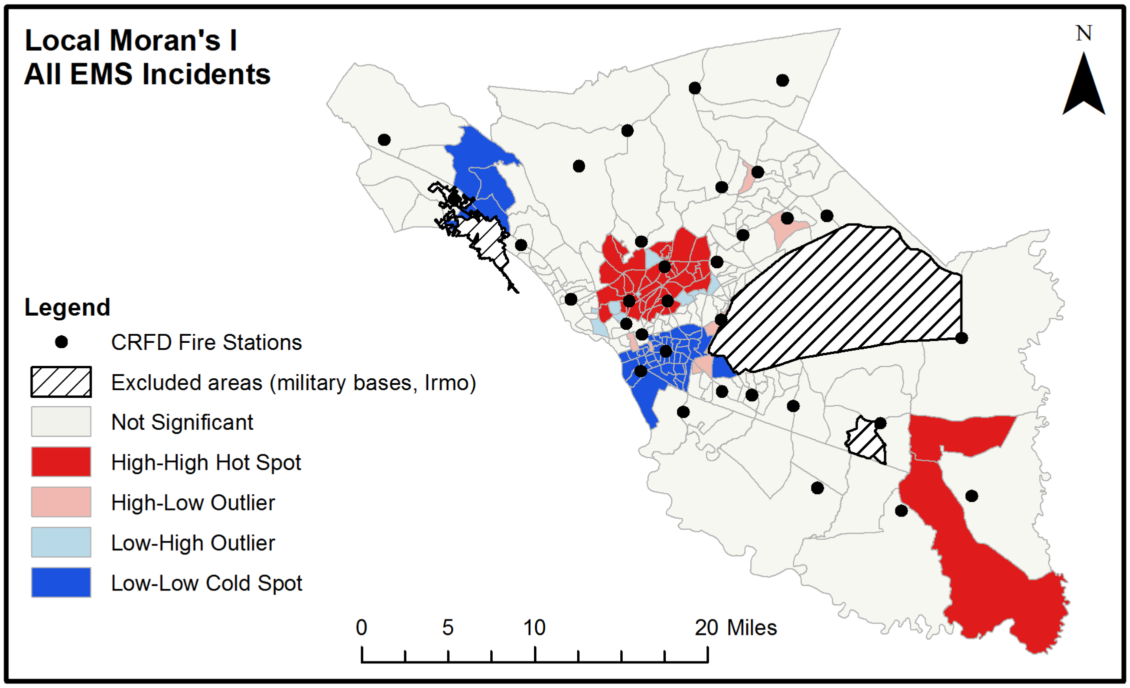

Figure 4.1: Local Moran's I for all EMS incidents

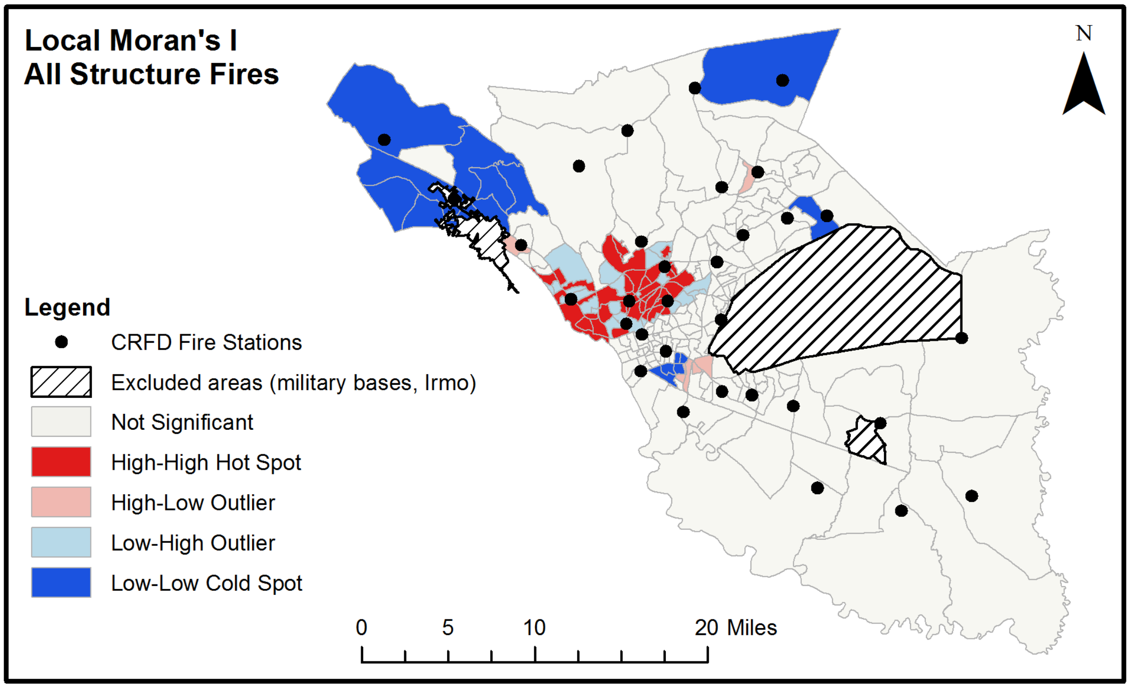

Figure 4.2: Local Moran's I for all structure fire incidents

The three types with a limited number of incidents (CO, fire fatalities, fire injuries) tended more towards single or small groups of high and low outlier block groups (Figure 4.3, Figure 4.4, Figure 4.5). Most of the statistically significant block groups at either extreme were located in the north central part of Columbia and Richland County or in Lower Richland. Low outliers were more common in the northern areas, and high outliers in Lower Richland, although there were exceptions to both of these.

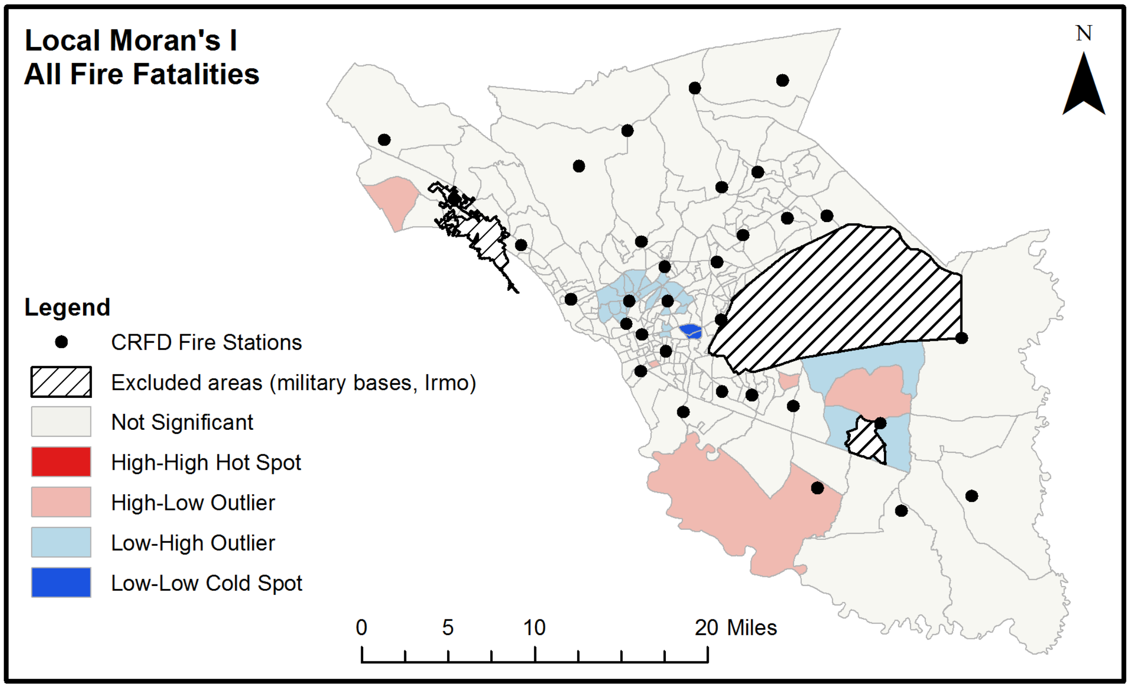

Figure 4.3: Local Moran's I for fire fatalities

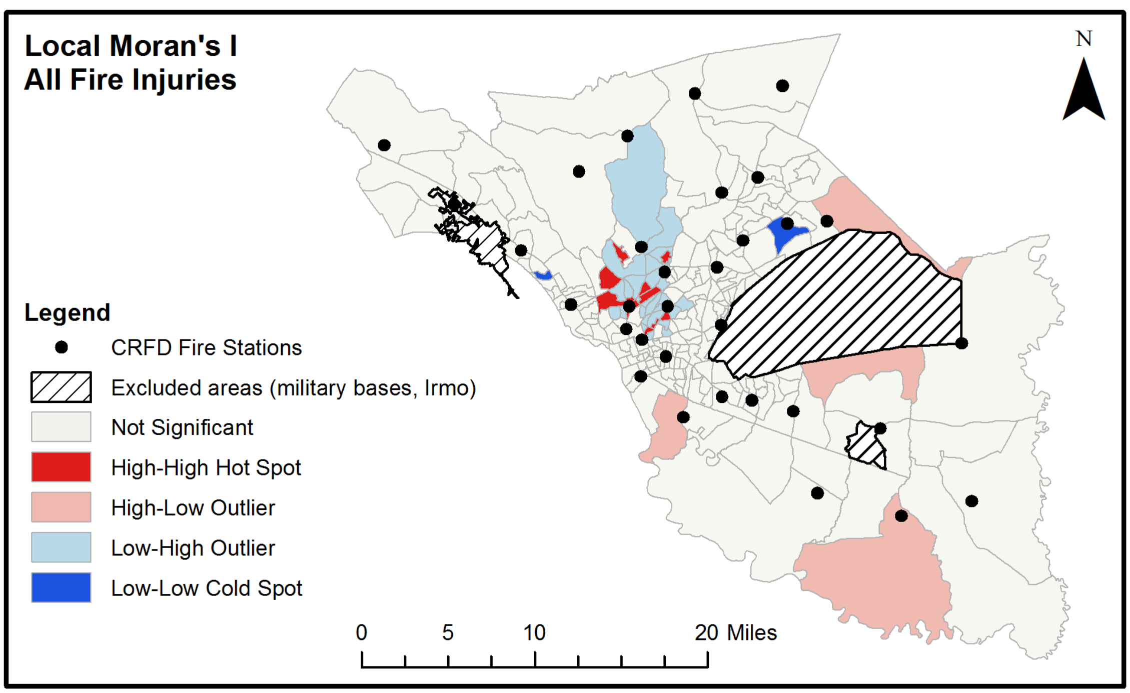

Figure 4.4: Local Moran's I for fire injuries

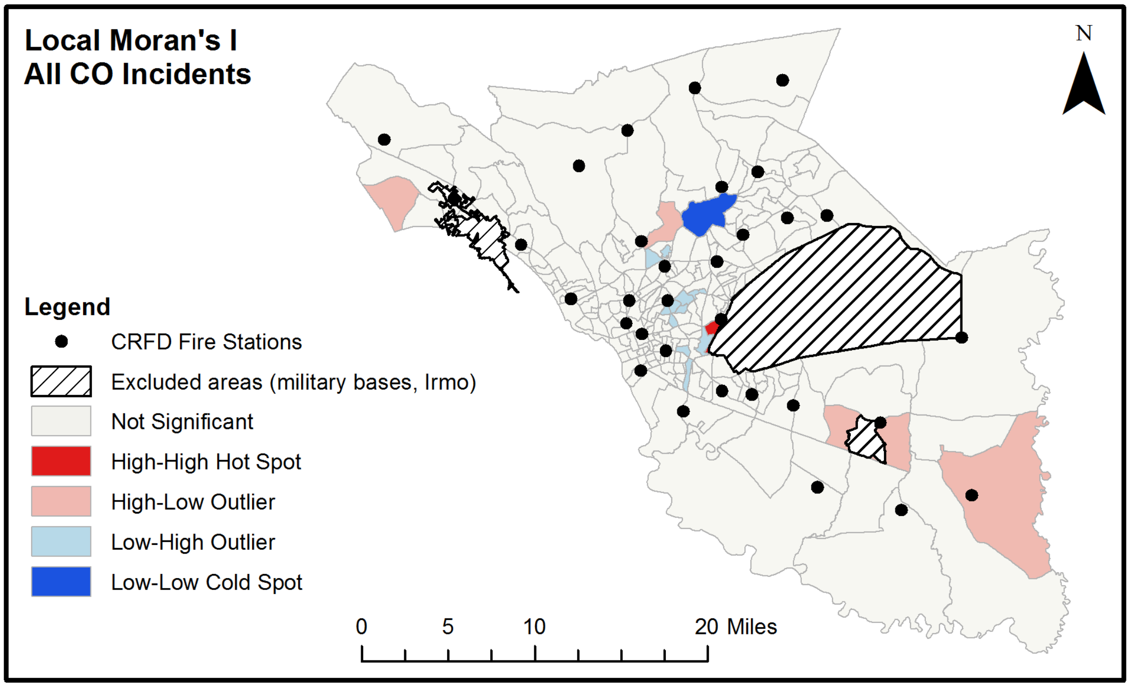

Figure 4.5: Local Moran's I for CO incidents

4.1.2 Mapping of Incident Rates

Mapping of annual incident rate per 10,000 people for EMS and all fire incidents showed regions of high rates in north central Columbia and Richland County and in Lower Richland (Figure 4.6, Figure 4.7). Almost every block group had multiple structure fires and many EMS incidents over the study period. The thematic maps for fire fatality, fire injury, and CO incident rates were far more pockmarked in appearance, since many block groups had none of these types of incidents (Figure 4.8, Figure 4.9, Figure 4.10). While annual incident rates can be a great way of accounting for population differences between block groups when assessing frequent incidents that occur multiple times a year, they can be a little more challenging when dealing with rare incidents. A rare type of incident may have a long-time average rate of less than one incident over the analysis time period. For example, it is overly optimistic to think that a block group with no fire fatalities in the seven-year period under analysis has never and will never have any fire casualty. More likely it just has a long-term rate of less than one fatality per seven years (e.g., one per decade for that size of population). Correspondingly the neighboring block group with a similar sized population who did have one fatality within the seven years potentially has a similar long-term incident rate, but their one fatality per decade happened to occur within the study period. The first block group will appear to have a fatality rate of zero, whereas the second block group will appear to have a fatality rate higher than it actually does. This kind of difference is exaggerated in block groups with small populations. This type of potential over and under emphasis of incident rate was most apparent with fire fatalities, as there were fewer fire fatalities than any other type of incident, with twenty-two fatalities spread over eighteen of the two hundred forty-five block groups in the county.

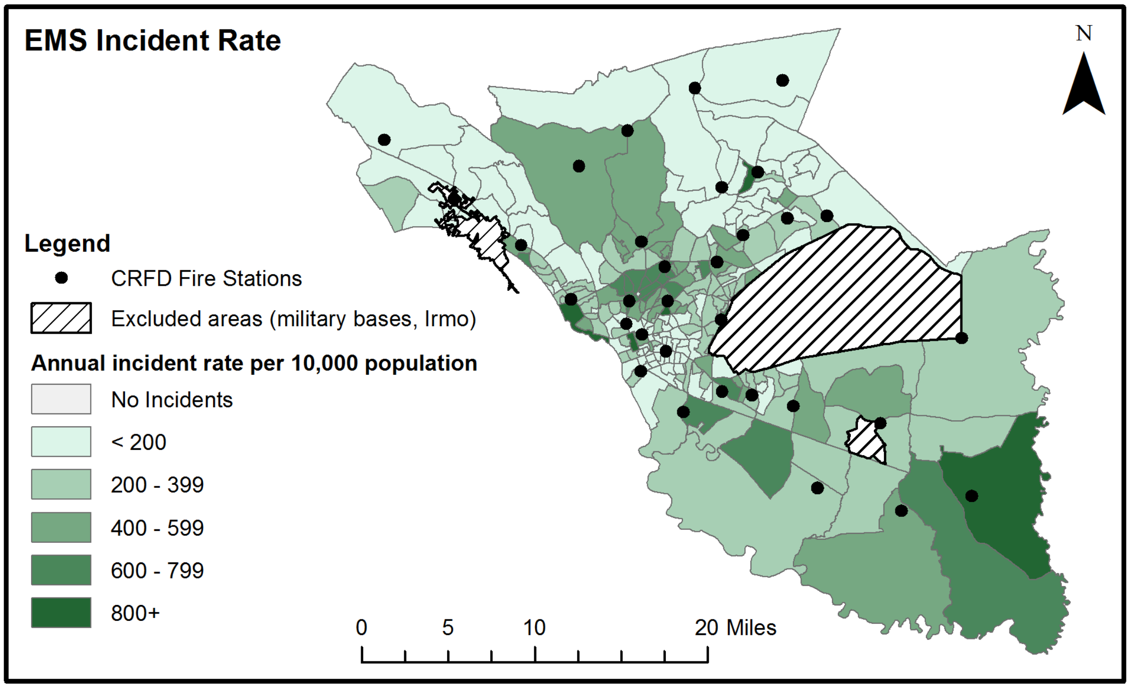

Figure 4.6: EMS incident rate

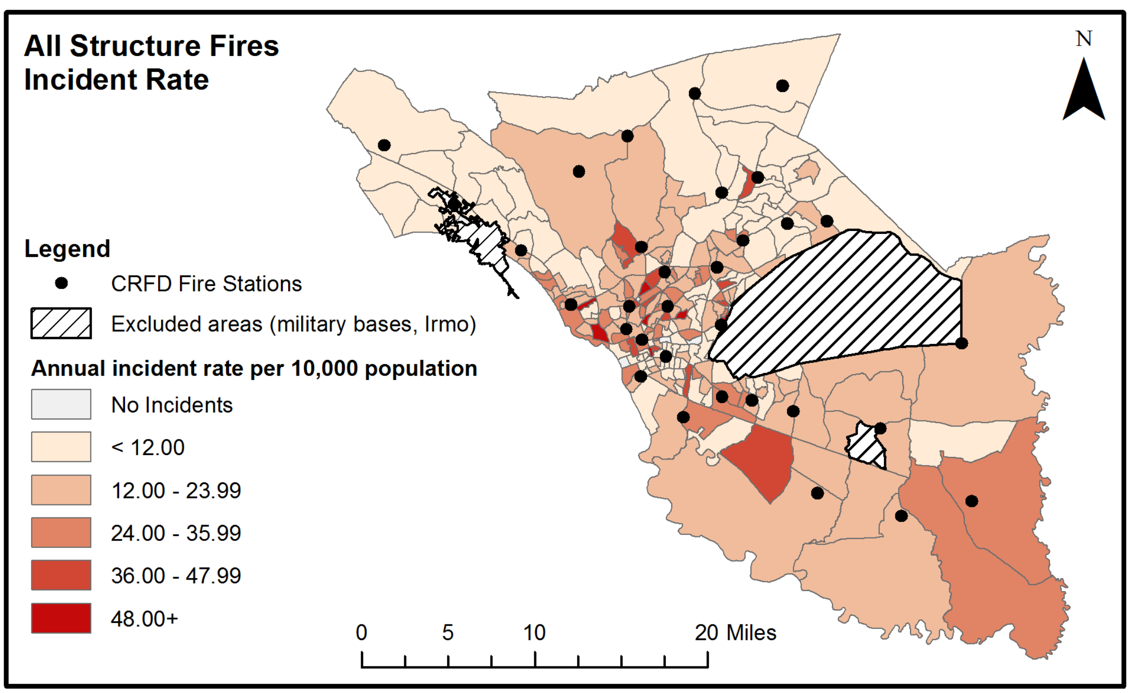

Figure 4.7: Structure fire incident rate

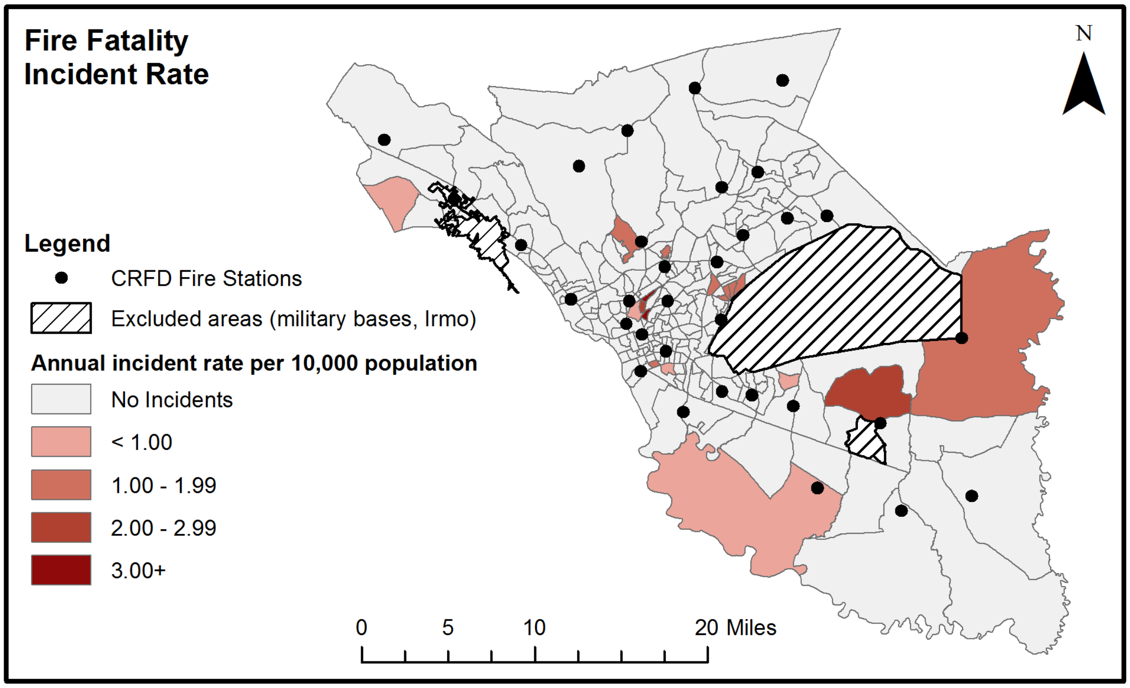

Figure 4.8: Fire fatality incident rate

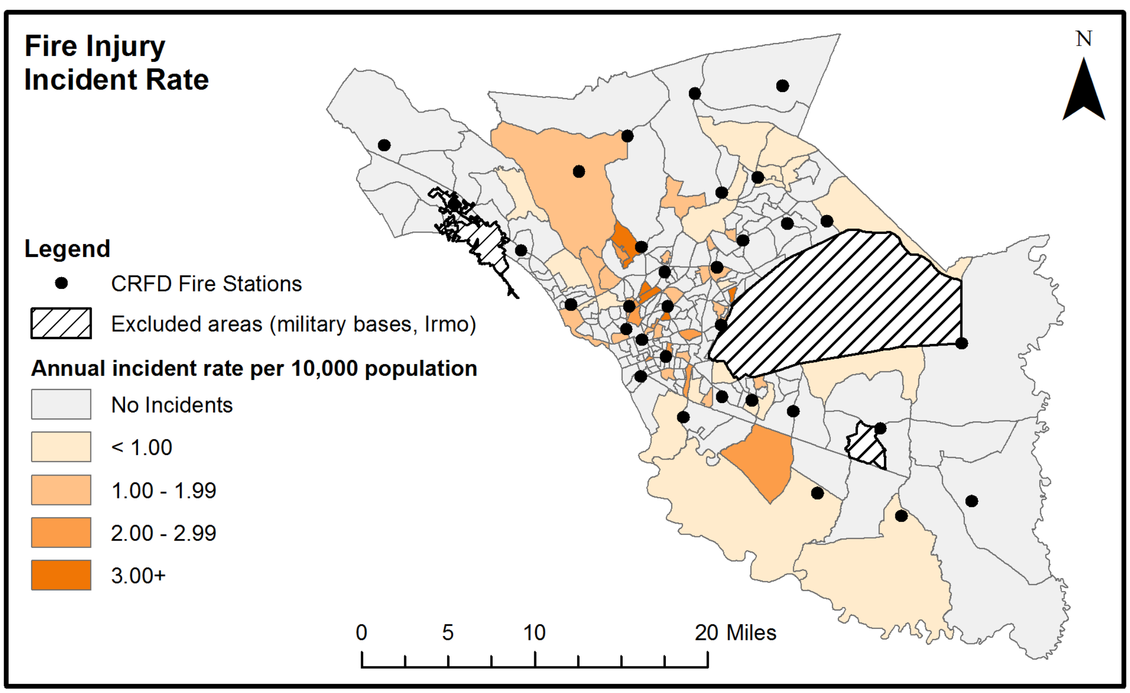

Figure 4.9: Fire injury incident rate

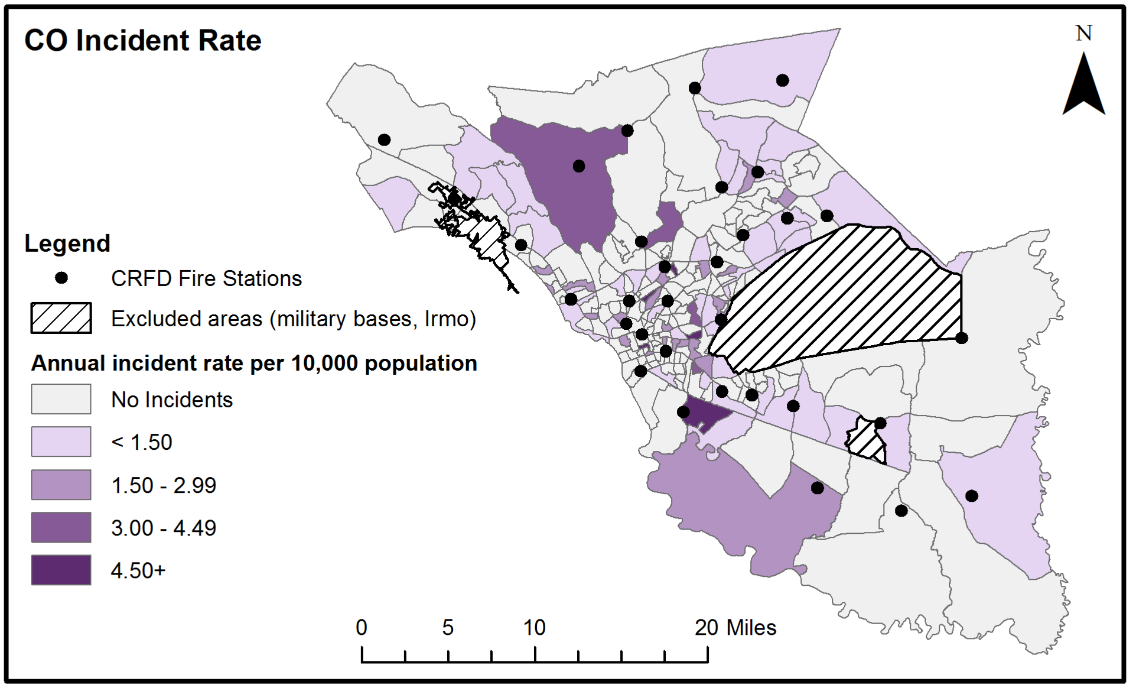

Figure 4.10: CO incident rate

4.1.3 <u>Comparison of Incident Distribution Results</u>

Comparison between Local Moran's I results and mapping the incident rate per 10,000 people per year for each type of call showed that when there is a large number of incidents (e.g., EMS, all fire incidents) similar hot and cold spots appear in both types of results. In contrast with a limited number of incidents, and thus many block groups without any of that type of incident, hot/cold spots and outliers do not necessarily highlight those block groups with the highest incident rates. Instead, they are more reflective of the geographical position of neighboring block groups without any incidents of the given type (Figure 4.8, Figure 4.9, Figure 4.10). This is particularly true in less densely populated areas with larger and more spread out block groups. For these reasons, hot spot algorithms may have limited use in accurately analyzing incident types with a low call volume. The combination of Local Moran's I with thematic maps of incident rates proved a more insightful way to answer Research Question 1 (i.e., the spatial variability of incidents) than either method used alone.

4.2 Factors Influencing Spatial Distribution of Incidents

The second research question considers how do underlying community variations in physical and social risk factors correlate with each other and with the different types of incidents. PCA was used to reduce a large number of risk variables into a more manageable set of related factors. Correlation analysis was used to identify which risk factors had statistically significant correlations with each type of incident, using both the original individual risk factors as well as the PCA primary factor output. K-means took the PCA output and broke block groups into clusters based on shared patterns of risk factors.

4.2.1 Reduction of Risk Factors using PCA

All versions of PCA explained between 67-72% of the variance with eight or nine principal factors (Appendix B Table B.1). The trial highlighted in Table B.1 had the greatest explained variance at 71.207%. It divided age into under 18 years, 18 to 50 years, and over 50 years, defined under education as those with less than a high school diploma or GED, and used total alcohol and smoking product sales data. The rotated component matrix for this trial (Table 4.1) highlights the most important variables for each factor, as is summarized in Table 4.2. In this table major loadings are defined as those with an absolute correlation greater than 0.5. Minor loadings had absolute correlations between 0.4 and 0.5. The spatial distribution of each factor varied greatly, with some factors highlighting extremes in single block groups, whereas other factors tended to have broader spatial patterns in their extremes (Figure 4.11, Figure 4.12, Figure 4.13, Figure 4.14, Figure 4.15, Figure 4.16, Figure 4.17, Figure 4.18, Figure 4.19). Some of these groupings, such as those related to age, race and ethnicity, and housing stock, show similar patterns of risk factors to what has been found in broader assessments of hazard vulnerability (Cutter, Boruff, and Shirley 2003). For example, Factor 1, which highlights a combination of risk factors related to systematic racism (Figure 4.11). Others, like Factor 3, identify other challenges related to emergency incident vulnerability such as access to emergency resources that is explained by the urban-rural variation in the county (Figure 4.13).

Table 4.1: Rotated component matrix for best PCA run

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9
Engine Distance	-0.016	0.137	0.767	0.269	0.12	-0.1	0.078	0.086	-0.029
Ladder Distance	-0.055	0.098	0.769	0.305	0.119	-0.217	-0.077	-0.067	0.053
Water Supply	0.021	0.016	0.843	0.122	-0.06	0.035	0.012	-0.058	-0.068
Railroad Grade Crossings	-0.089	-0.295	0.39	-0.049	-0.02	0.354	-0.176	0	-0.352
Alcoholic Beverages	-0.237	0.171	0.072	0.891	0.089	-0.075	-0.016	0.065	0.009
Smoking Products	-0.156	0.137	0.155	0.888	0.075	-0.056	-0.01	0.088	0.015
Owner Occupied	-0.297	0.748	0.245	0.176	0.128	-0.255	-0.086	-0.049	-0.116
Vacant	0.187	-0.132	-0.012	0	0.01	0.754	-0.023	0.033	0.172
Crowded	0.264	-0.262	0.071	-0.044	0.491	0.227	0.053	0.23	-0.031
No Diploma	0.673	0.104	0.176	-0.234	-0.079	0.202	0.219	0.118	-0.047
Single Parents	0.688	-0.082	-0.117	0.014	0.14	0.123	-0.092	-0.02	-0.04
Poverty	0.481	-0.278	0.019	-0.151	0.116	0.608	-0.076	0.003	-0.063
Under 18	0.176	0.049	0.058	0.23	0.867	-0.113	0.072	-0.101	-0.093
Age 18 to 49	-0.155	-0.422	-0.062	-0.071	-0.777	0.134	0.023	0.064	0
Over 50	0.048	0.792	0.089	-0.135	-0.059	-0.042	-0.184	0.024	0.169
White	-0.898	0.06	-0.012	0.079	-0.166	0.131	-0.016	0.032	-0.049
Black	0.896	-0.013	0.025	-0.087	0.177	-0.108	-0.106	-0.175	0.013
Native American	-0.046	-0.103	-0.042	-0.071	-0.101	0.065	0.057	0	0.758
Asian	-0.135	-0.176	-0.06	0.065	-0.048	-0.071	-0.054	0.824	0.091
Other/Two+ Races	0.034	-0.101	-0.023	0.007	-0.023	-0.068	0.829	0.098	0.003

Hispanic	-0.075	-0.213	-0.003	-0.026	0.014	-0.221	0.775	0.106	-0.135
One/Two Family	-0.071	0.799	-0.072	0.163	0.144	-0.045	-0.063	-0.173	-0.282
Multi Family	0.077	-0.656	-0.223	0.005	0.058	0.246	-0.091	0.304	0.413
Mobile Home	0.151	0.047	0.779	-0.116	0.016	0.052	0.151	-0.046	0.006
Vehicle Home	0.025	0.052	0.137	0.065	0.066	0.169	0.628	-0.033	0.165
No Insurance	0.632	0.003	0.026	-0.109	-0.28	0.079	0.186	0.098	-0.039
Medicaid/care Insurance Only	0.727	-0.007	0.048	-0.229	0.399	0.064	-0.06	0.021	-0.031
Poor English	0.074	-0.02	-0.002	-0.034	0.003	0.006	0.215	0.825	-0.039
Old House	-0.245	0.024	-0.206	-0.099	-0.214	0.625	-0.032	-0.115	-0.105
Postwar House	0.241	0.502	-0.32	-0.51	0.146	0.203	-0.009	0.103	-0.09
Late 20th Cen. House	-0.062	-0.223	0.407	0.184	0.111	-0.337	-0.16	0.136	0.424
Early 21st Cen. House	-0.059	-0.194	0.181	0.775	0.094	-0.002	0.081	-0.093	-0.098
Disabled Household	0.527	0.509	0.005	-0.024	0.127	0.083	-0.073	-0.047	0.121

Major loadings were those with a value less than -0.5 (negative loading) or greater than 0.5 (positive loading). Minor loadings were those with a value between from 0.4 up to 0.5, either negative (-0.4 to -0.5) or positive (0.4 to 0.5).

Table 4.2: Principal factors of PCA run with highest explained variance

Factor	Factor Name	Positive Loadings	Negative Loadings	% Variance Explained
Factor 1	Systematic Hard Times	Black, Medicaid/care Insurance, Single Parents, No Diploma, No Insurance, Disabled Minor: Poverty	White	17.166
Factor 2	Older Homeowners	One/Two Family House, Over 50, Owner Occupied, Disabled, Postwar House	Multi Family Minor: Age 18 to 49	13.900
Factor 3	Rural	Water Supply, Mobile Home, Ladder Distance, Engine Distance, Minor: Late 20th Cen. House		10.959
Factor 4	Lifestyle Choices	Alcohol, Smoking, Early 21st Cen. House	Postwar House	6.604
Factor 5	Kids	Under 18 Minor: Crowded, Medicaid/care Insurance	Age 18 to 49	6.392
Factor 6	Abandoned Buildings	Vacant, Old House, Poverty		4.958
Factor 7	Multiracial and Ethnic	Other/Two+ Races, Hispanic, Vehicle Home		4.344
Factor 8	Recent Asian Immigrants	Poor English, Asian		3.725
Factor 9	Native American	Native American Minor: Late 20th Cen. House, Multi Family		3.159

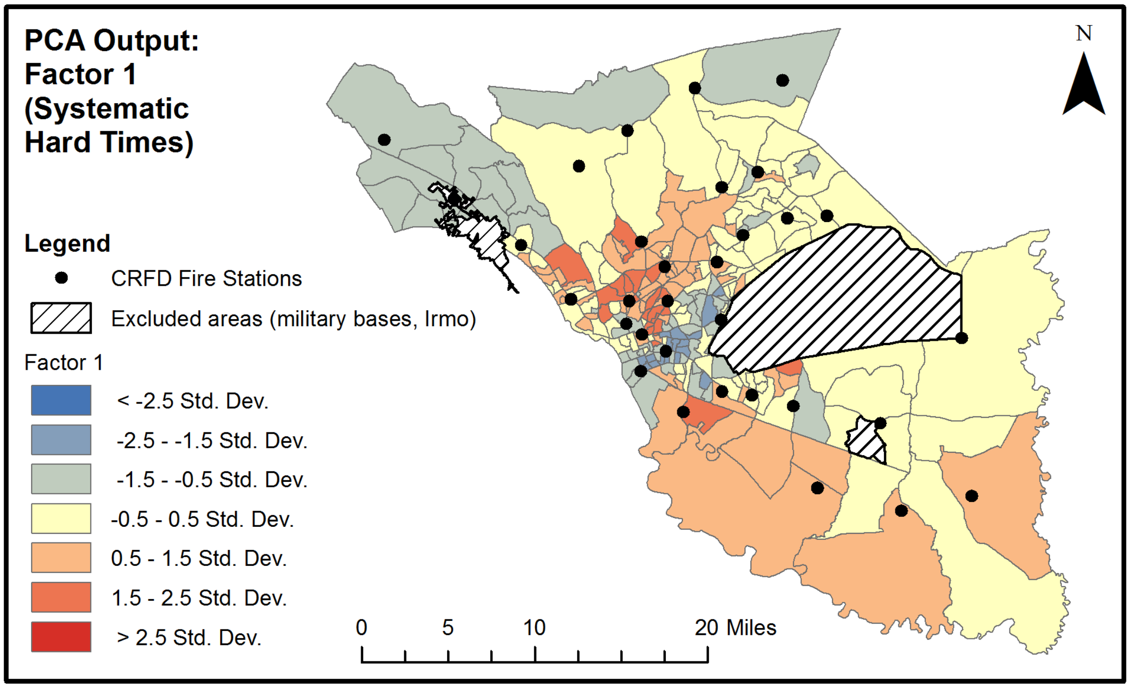

Figure 4.11: PCA Factor 1 (Systematic Hard Times)

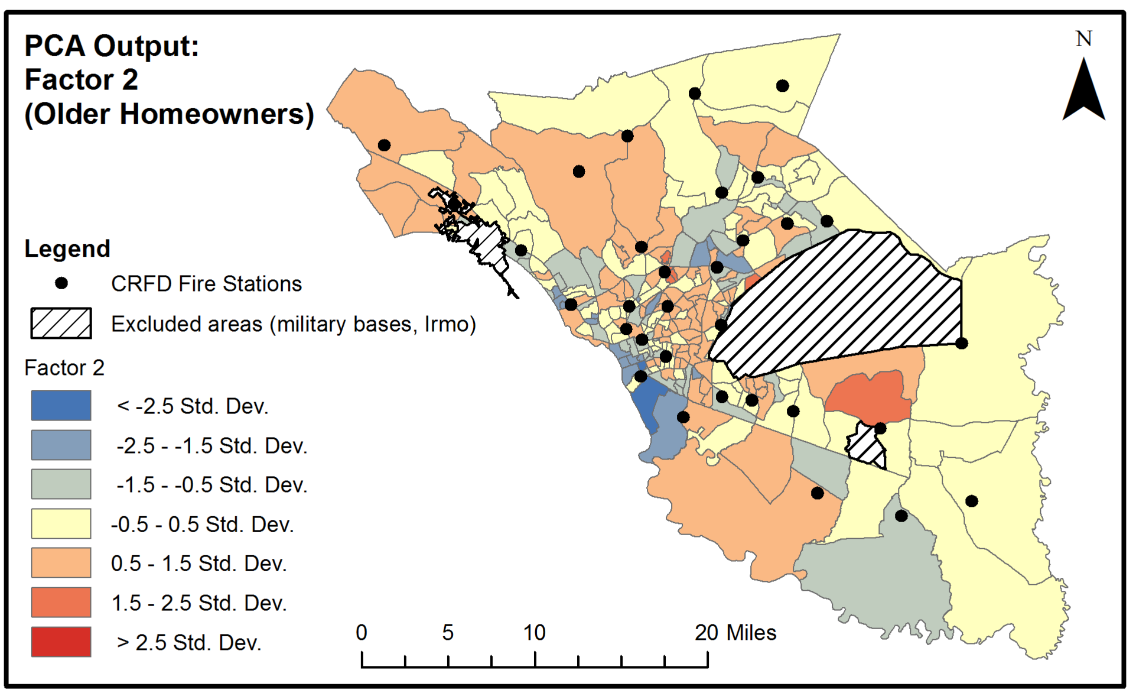

Figure 4.12: PCA Factor 2 (Older Homeowners)

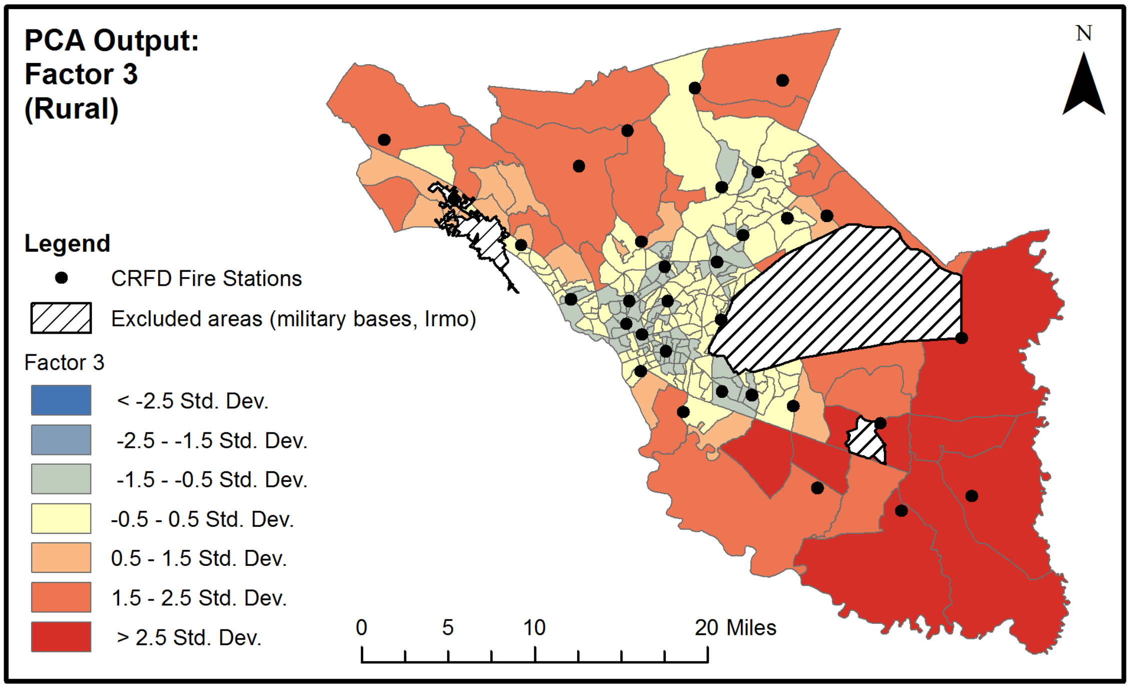

Figure 4.13: PCA Factor 3 (Rural)

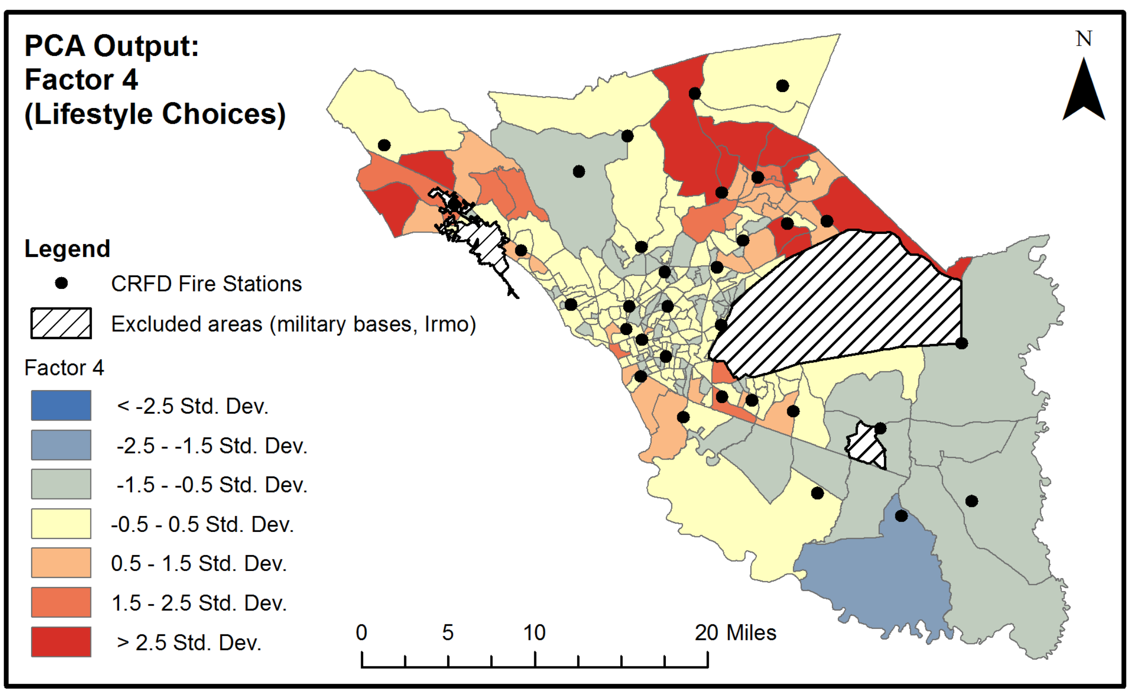

Figure 4.14: PCA Factor 4 (Lifestyle Choices)

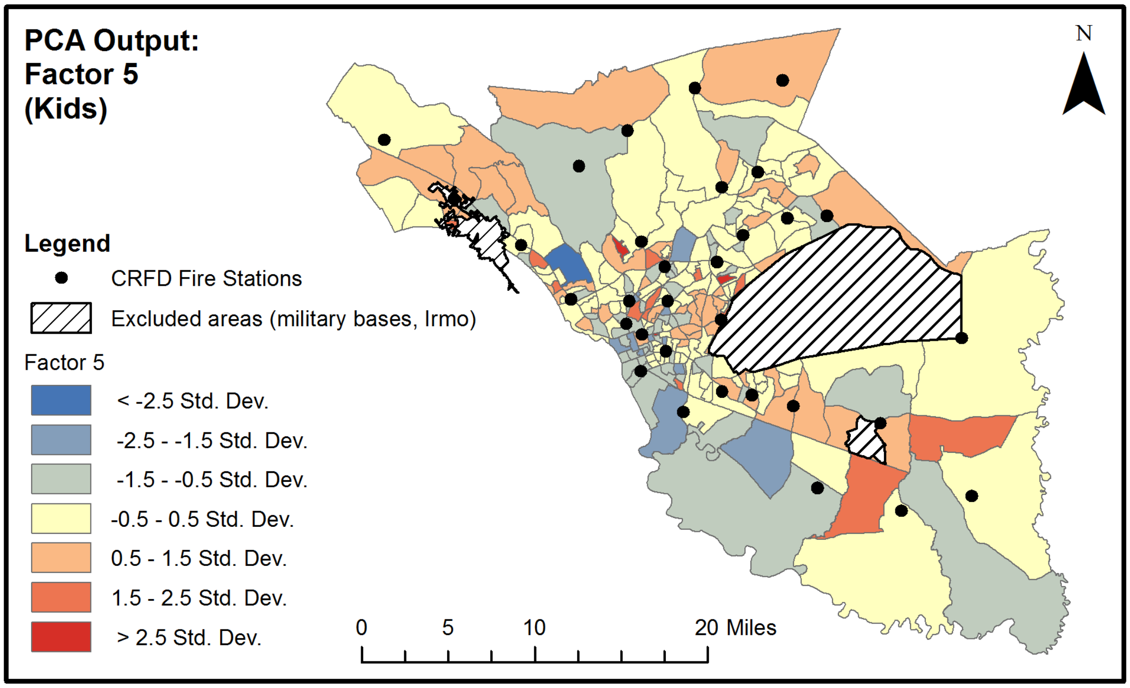

Figure 4.15: PCA Factor 5 (Kids)

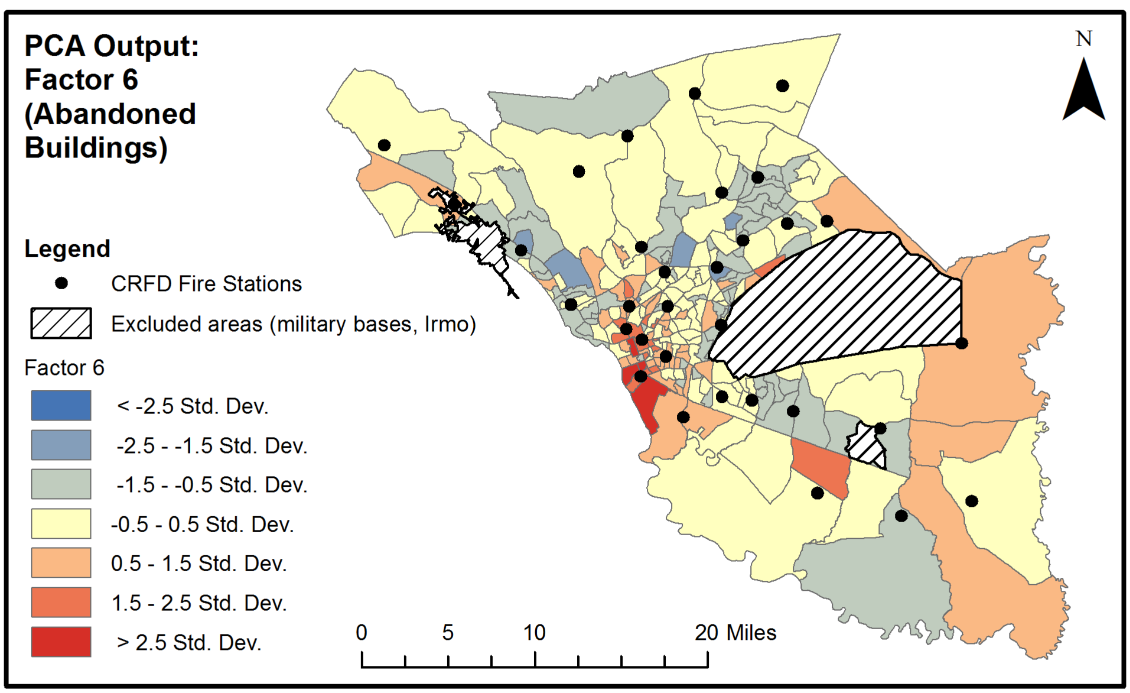

Figure 4.16: PCA Factor 6 (Abandoned Buildings)

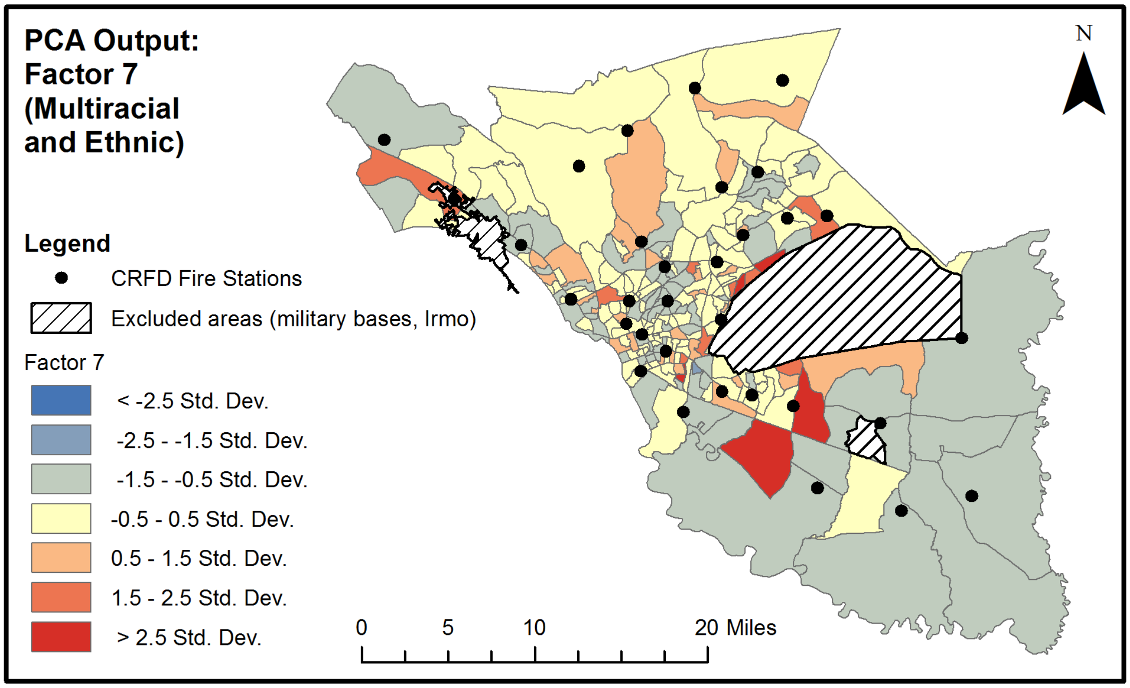

Figure 4.17: PCA Factor 7 (Multiracial and Ethnic)

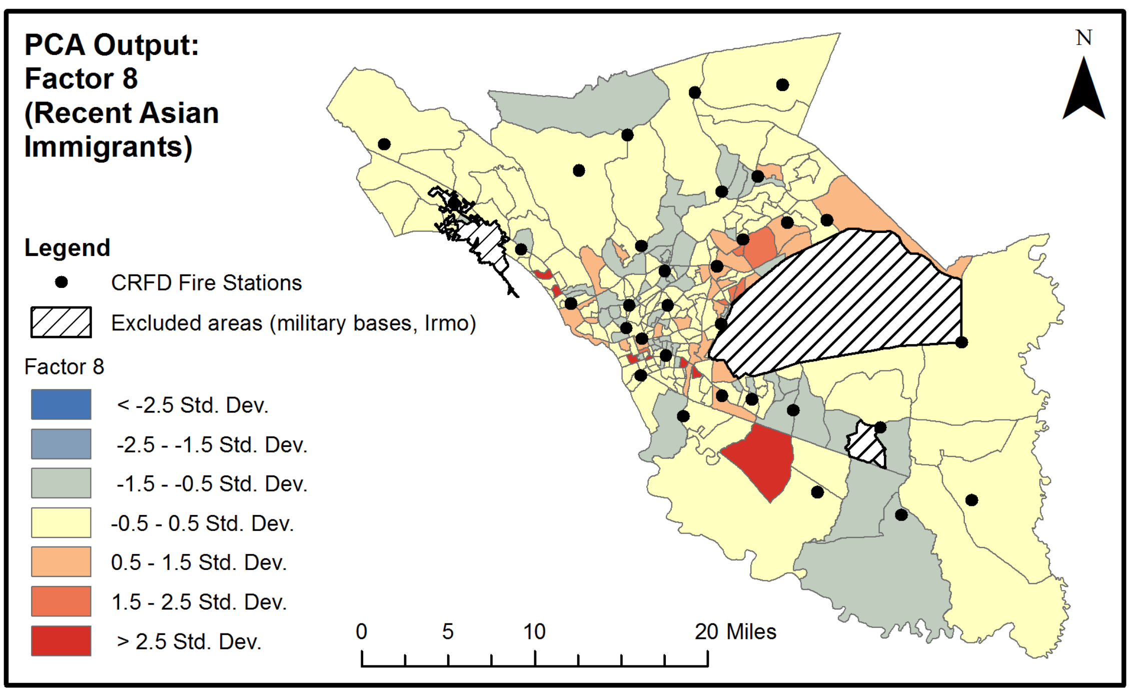

Figure 4.18: PCA Factor 8 (Recent Asian Immigrants)

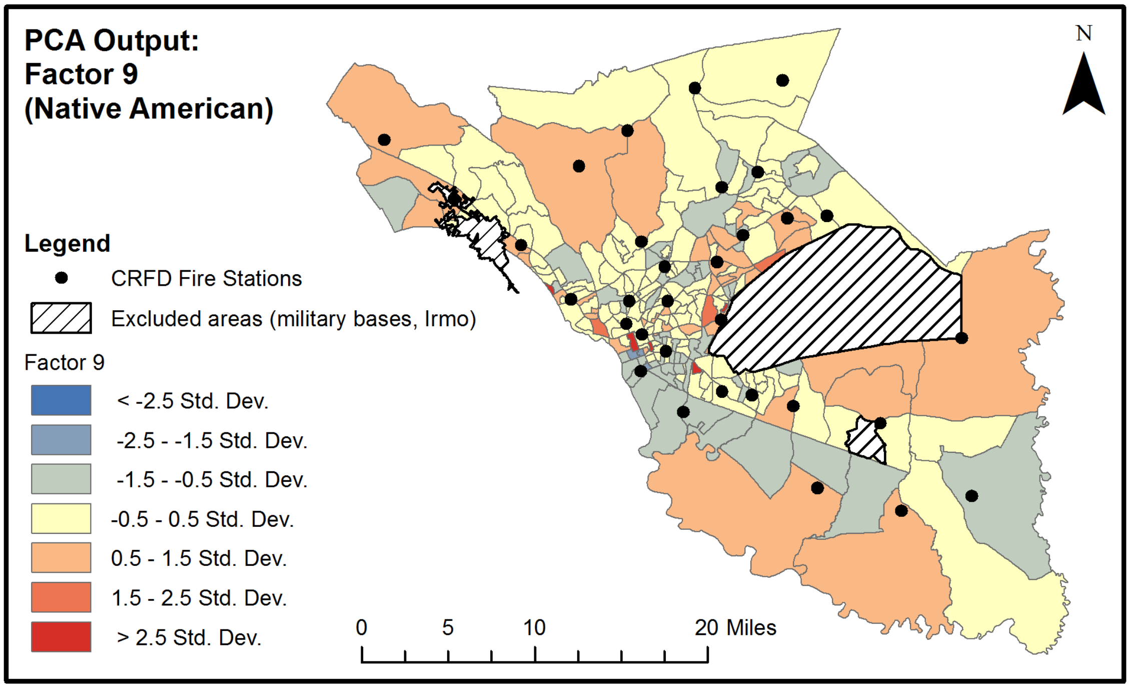

Figure 4.19: PCA Factor 9 (Native American)

4.2.2 Correlations Between Risk Factors and Incidents

Correlation analysis and significance testing of the output Pearson r-values showed significant correlation between many risk variables and one or more types of incidents (Table 4.3). Because of the large sample size, correlation was significant despite being at most of low to moderate strength. There was a wide range of variation in overall significance depending on the risk variable. Scatter plots crossing each variable and PCA factor against each incident type were made to test whether or not the relationship was linear. In most cases significant correlation appeared to be at least vaguely linear, with most nonsignificant correlations showing no visual pattern. In a few cases, primarily with alcohol and tobacco, there was a clear nonlinear relationship visible (Figure 4.20). As a non-spatial method, classical correlation analysis was only able to identify overall patterns, not risk variables with significant correlation in only a few block groups. Significance testing was also less helpful in determining which thresholds to use for age and under education. All possible thresholds for old age and under education showed high levels of significance, so there was not an obvious cut-off to use based on correlation analysis.

Table 4.3: Pearson correlation of risk variables with incident types

	All Incidents	All Fires	All EMS	All CO	Fire Fatalities	Fire Injuries	Fire No Casualties
Engine Distance	-0.149*	-0.200**	-0.143*	-0.042	0.013	-0.022	-0.204**
Ladder Distance	-0.040	-0.183**	-0.030	-0.070	-0.043	-0.130*	-0.178**
Water Supply	0.023	-0.088	0.030	-0.050	-0.011	-0.008	-0.090
Grade Crossings	-0.023	-0.055	-0.020	-0.038	0.000	-0.073	-0.052
Alcoholic Beverages (Total)	-0.255***	-0.277***	-0.248***	0.000	-0.087	-0.113	-0.273***
Alcoholic Beverages (Household Average)	-0.310***	-0.339***	-0.303***	0.108	-0.075	-0.122	-0.337***
Smoking Products (Total)	-0.183**	-0.217***	-0.177**	0.017	-0.085	-0.087	-0.213***
Smoking Products (Household Average)	-0.098	-0.185**	-0.091	0.184**	-0.043	-0.031	-0.185**
Owner Occupied	-0.112	-0.268***	-0.101	0.097	-0.048	-0.068	-0.269***
Vacant	0.313***	0.373***	0.303***	-0.010	0.118	0.056	0.373***
Crowded	0.046	0.074	0.043	-0.092	0.101	0.049	0.068
Under 8th Grade Education	0.205**	0.132*	0.206**	-0.081	0.092	-0.008	0.132*
No Diploma	0.374***	0.326***	0.369***	-0.062	0.196*	0.134*	0.316***
Single Parents	0.337***	0.386***	0.327***	-0.004	0.085	0.126*	0.384***
Poverty	0.293***	0.332***	0.285***	-0.034	0.11	0.164*	0.325***
Under 5	-0.070	0.020	-0.074	-0.051	0.048	0.006	0.018
Under 10	-0.047	0.052	-0.052	-0.063	0.078	0.030	0.048

Under 18	-0.034	0.049	-0.038	-0.050	0.092	0.036	0.043
Age 6 to 49	-0.276***	-0.082	-0.281***	-0.183**	-0.079	-0.082	-0.075
Age 18 to 49	-0.238***	-0.096	-0.242***	-0.143*	-0.112	-0.092	-0.087
Age 6 to 69	-0.142*	-0.035	-0.145*	-0.150*	-0.059	-0.047	-0.030
Age 18 to 69	-0.096	-0.059	-0.096	-0.080	-0.105	-0.062	-0.052
Age 20 to 69	0.120	0.174**	0.114	0.050	-0.029	0.042	0.177**
Over 50	0.296***	0.075	0.302***	0.198**	0.063	0.080	0.069
Over 65	0.196**	0.022	0.202**	0.181**	0.033	0.042	0.018
Over 70	0.197**	0.024	0.203**	0.195**	0.034	0.047	0.021
Over 75	0.175**	0.046	0.178**	0.181**	0.057	0.059	0.041
Over 80	0.130*	0.029	0.133*	0.096	-0.005	0.033	0.028
Over 85	0.117	0.014	0.121	-0.006	-0.022	0.047	0.013
White	-0.480***	-0.449***	-0.472***	-0.026	-0.121	-0.168**	-0.445***
Black	0.491***	0.441***	0.484***	0.036	0.121	0.167**	0.436***
Native American	0.199**	0.220***	0.194**	-0.022	-0.033	-0.050	0.231***
Asian	-0.084	0.002	-0.088	0.082	0.026	0.024	-0.001
Other/Two+ Races	-0.087	-0.048	-0.086	-0.146*	-0.038	-0.031	-0.045
Hispanic	-0.151*	-0.111	-0.150*	-0.115	-0.047	-0.042	-0.109
One/Two Family	-0.066	-0.205**	-0.057	0.073	0.019	0.017	-0.212***
Multi Family	0.117	0.326***	0.102	-0.020	0.011	0.013	0.333***
Mobile Home	0.197**	0.094	0.199**	0.000	-0.013	0.047	0.094
Vehicle Home	-0.044	0.058	-0.049	-0.005	-0.022	-0.026	0.062
No Insurance	0.274***	0.213***	0.273***	-0.091	0.034	0.225***	0.204**
Medi-caid/care Insurance Only	0.409***	0.368***	0.403***	-0.016	0.207**	0.187**	0.356***
Poor English	0.042	0.102	0.037	0.007	-0.015	0.062	0.102
Old House	-0.064	-0.006	-0.066	0.007	0.024	-0.029	-0.006

Postwar House	0.301***	0.305***	0.294***	0.123	0.161*	0.210***	0.293***
Late 20th Cen. House	-0.030	-0.038	-0.029	-0.013	-0.095	-0.096	-0.028
Early 21st Cen. House	-0.196**	-0.204**	-0.191**	-0.089	-0.112	-0.117	-0.197**
Disabled Household	0.356***	0.234***	0.356***	0.025	0.146*	0.233***	0.219***

*p<.05, **p<.01, ***p<0.001

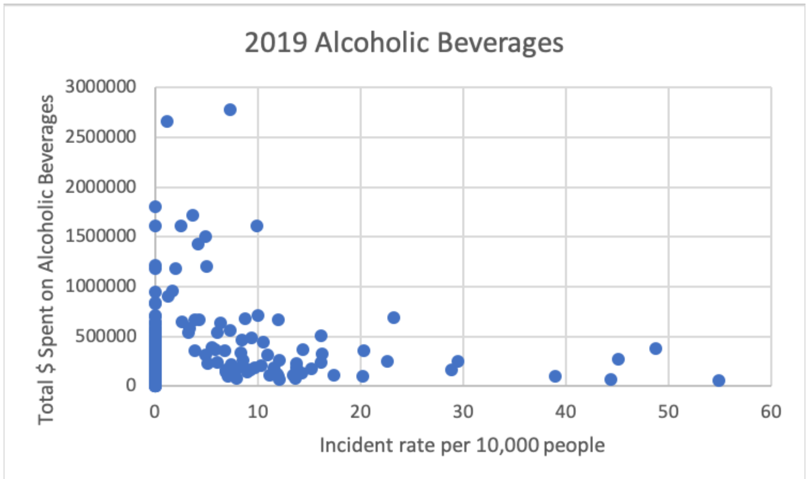

Figure 4.20: Scatter plot of alcohol usage against CO incident rates

Correlation analysis was more helpful in identifying patterns between individual incident types and the PCA output factors (Table 4.4), although significant correlation was still at most moderate in strength. Factor 1 had significant correlation with all fire and medical incidents, but not with CO calls alone. Factor 2 had significant correlation with medical and CO calls, but not with any type of fire incident. Factors 4, 6, and 9 were significant with the four most common types of incidents – all incidents, medical incidents, all structure fires, and no casualty fires. Factor 7 had significant correlation only with CO calls. Factors 3, 5, and 8 were not significant with any type of incident. Due to the large percentage of medical calls within the total calls overall, significant correlation with all incidents combined followed the exact same patterns significant correlation with medical calls. Similarly, all structure fires and no casualty structure fires showed the same patterns in correlation significance with the nine PCA factors.

Table 4.4: Pearson correlation of PCA factors with incident types

	All Incidents	All Fires	All EMS	All CO	Fire Fatalities	Fire Injuries	Fire No Casualties
Factor 1	0.501***	0.442***	0.495***	-0.022	0.133*	0.228***	0.433***
Factor 2	0.144*	-0.028	0.151*	0.145*	0.066	0.096	-0.038
Factor 3	0.068	-0.063	0.074	-0.038	-0.009	-0.036	-0.062
Factor 4	-0.177**	-0.179**	-0.173**	-0.041	-0.096	-0.086	-0.174**
Factor 5	-0.039	0.059	-0.044	0.003	0.112	0.002	0.054
Factor 6	0.161*	0.221***	0.154*	-0.007	0.109	0.056	0.218***
Factor 7	-0.113	-0.048	-0.114	-0.133*	-0.034	-0.020	-0.047
Factor 8	0.014	0.063	0.011	0.067	0.043	0.086	0.057
Factor 9	0.271***	0.306***	0.262***	0.047	-0.016	-0.022	0.316***

*p<.05, **p<.01, ***p<0.001.

4.2.3 Cluster Analysis (K-means)

K-means assembles block groups into nonspatial clusters based on common patterns of risk traits. Two versions of K-means were run; one on the original risk variables as recommended by the best PCA run, and the other on the PCA principal factors. Running K-means with the input parameter to recommend the optimal number of groups led three groupings when using the original risk variables and fourteen groupings based on principal factors. The three groupings with the original risk variables divided block groups into categories roughly representing dense city center, suburbia, and rural portions of the county (Figure 4.21). In contrast, using principal factors as inputs to create fourteen groupings led to a much more nuanced perspective on similarities between block groups (Figure 4.22). With this output clear patterns started to emerge regarding the shared traits of each group in terms of risk, as well as differences in incident frequency and location between the fourteen groups. Overlaying battalion boundaries on the K-means outputs shows that the risk factor groupings do not align with battalion boundaries. Each battalion contained between six and nine of the fourteen PCA-based K-means groupings. The most spatially clustered groupings, Groups 2 and 14, were split down the middle by battalion boundaries.

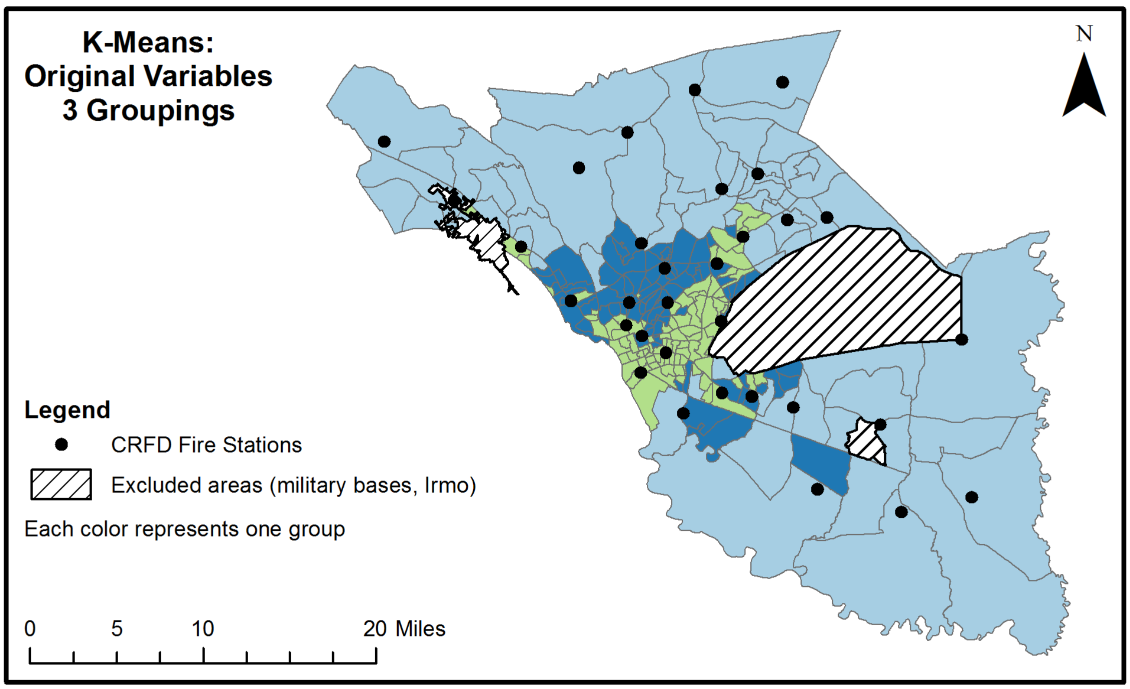

Figure 4.21: K-means used to divide block groups into three groups based on original risk variables

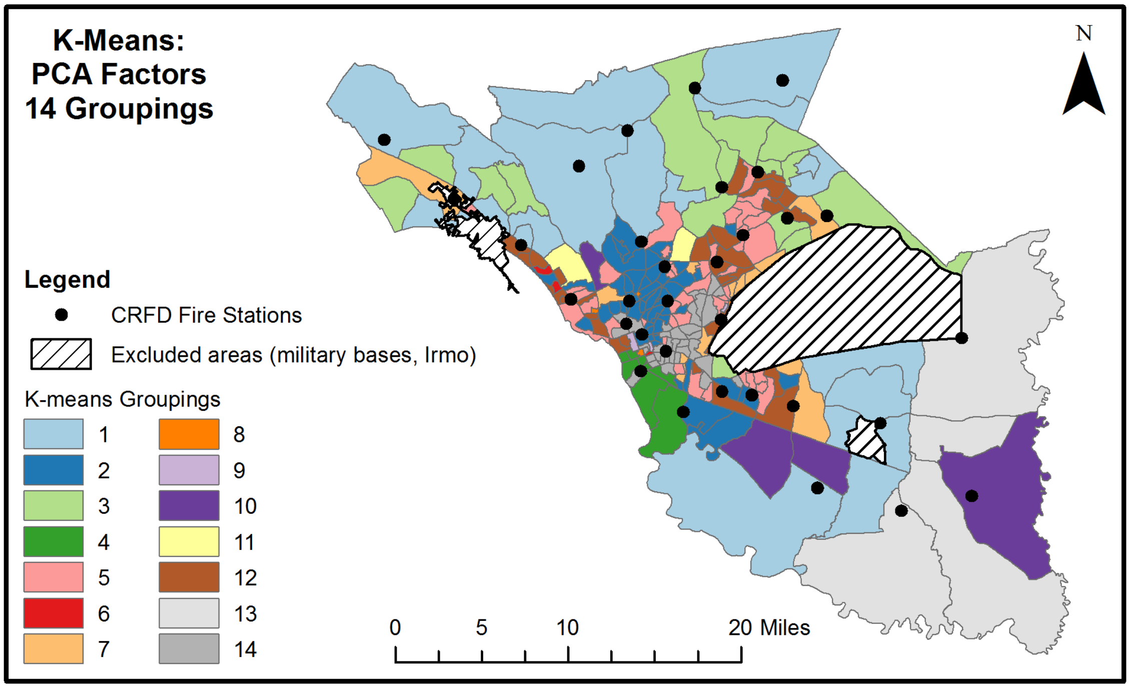

Figure 4.22: K-means used to divide block groups into fourteen groups based on PCA factors

4.3 Results Summary

Research Question 1, the spatial variability of the different types of incidents, was answered using Local Moran's I and thematic mapping of incident rates. Due to EMS incidents comprising a significant percentage of total incidents, these incident types tended to increase or decrease in concert and show nearly identical spatial patterns. A similar dynamic was observed in the number of no casualty fire incidents moving in tandem with total fire incidents. Hot spot analysis and thematic mapping showed similar patterns with clear hot and cold spots for the more frequent incident types (i.e., EMS, all structure fires). The main hot spots were in northern Columbia, with secondary hot spots in far Lower Richland. The less frequent incident types (i.e., fire fatalities, fire injuries, and CO incidents) resulted in a more pockmarked appearance in the thematic maps, with more outliers than hot spots in the hot spot analysis results. The combination of hot spot analysis and thematic mapping proved more useful for these incident types than either method alone.

Research Question 2 considers how underlying community variations in physical and social risk factors correlate with each other and with the different types of incidents. It was addressed using a combination of PCA, correlation analysis, and K-means analysis. PCA was used to reduce a few dozen risk variables into nine related primary factors, which were then used in correlation analysis and K-means. The nine principal factors were Systematic Hard Times, Older Homeowners, Rural, Lifestyle Choices, Kids, Abandoned Buildings, Multiracial and Ethnic, Recent Asian Immigrants, and Native American, in order of most to least explained variance. Correlation analysis identified which risk factors were correlated with each type of incident. Significant risk factors both alone and as PCA factors had low to moderate correlation with the different incident types. K-means was used to cluster block groups with similar patterns of risk factors. Using the nine PCA factors provided more nuance in the K-means results than using the original risk variables that went into the best PCA run (i.e., fourteen groupings instead of three). Overall a combination of methods was necessary to gain a full perspective on spatial distribution of risk factors across the county.

CHAPTER 5

DISCUSSION

Local Moran's I results show clear large hot spots in northern Columbia for all incidents combined, as well as EMS, overall fire, and no casualty fire incidents. The rarer types of incidents – fire fatalities, fire injuries, and CO incidents – had too few incidents for any major hot spots to appear. When compared with individual PCA factors the only factor that clearly aligns with the main hot spot in northern Columbia is Factor 1 (Figure 4.11). Viewing the maximum factor for each block group (Figure 5.1) doesn't highlight any additional patterns when compared with the Local Moran's I output and thematic maps of incident rates, but it provides some information about which risk variables are most important for a given block group or larger region. While groups of risk variables larger than single block groups are visible when looking at the maximum factors, K-means proved even more useful in eliciting patterns of risk variables, and in matching patterns in incident rates with co-located risk variable patterns. Overlaying battalion boundaries (Figure 3.1) on either the maximum factor data or the K-means groupings only showed that every battalion contains many different communities, none of which align with battalion boundaries. Finally, it is also worth considering limitations with this work not brought to light elsewhere in the work.

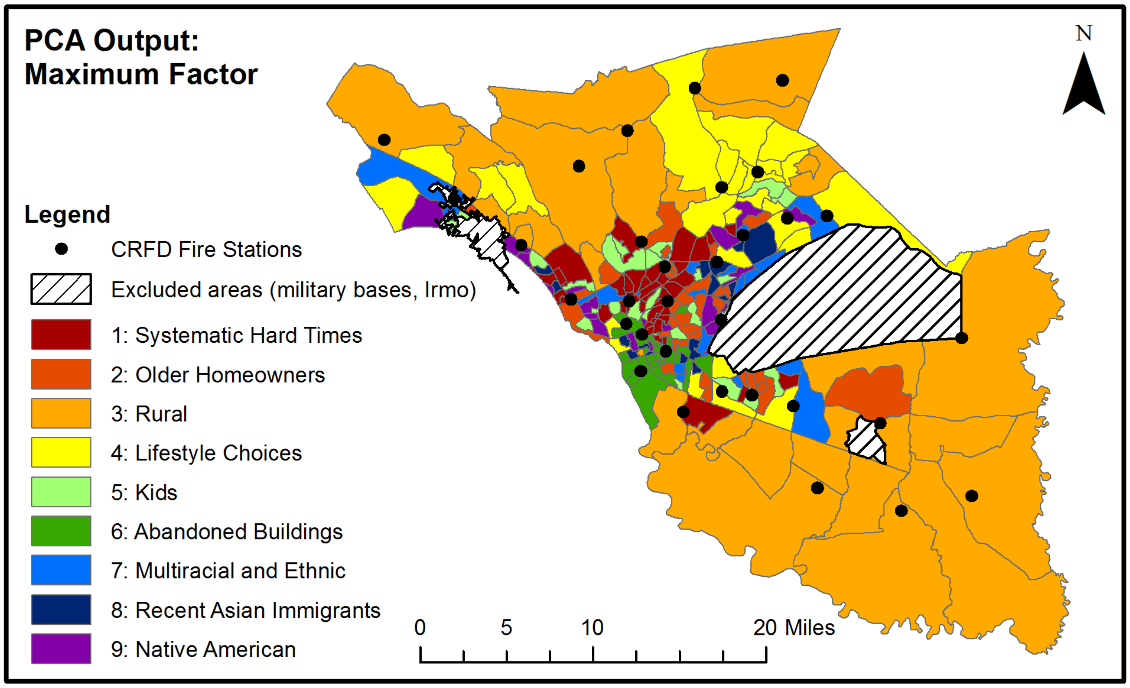

Figure 5.1: PCA output - factor with highest value for each block group

5.1 Comparison of K-means Groupings and Incident Rates

The K-means fourteen groupings based on PCA factors (Figure 4.22) showed clear patterns in terms of which individual factors influenced how block groups were grouped together. There were also clear differences in the annual incident rate per 10,000 people for each type of incident for each of the fourteen groups. Five groups (Groups 1, 3, 4, 8, and 11) had consistently below average incident rates, one consistently hovered around average (Group 5), one was consistently above average (Group 2), and seven had significant variability compared to the overall average rate depending on the type of incident (Groups 6, 7, 9, 10, 12, 13, 14). While there may have been shared patterns in high or low call volume, each individual group had distinctly different patterns in terms of prominent risk variables (Figure 5.2). Figure 5.2 shows the annual incident rate per 10,000 people for all incident types and each of the fourteen K-means groups, allowing for comparisons between each of the fourteen groups and against the overall average rate for each type of incident. Each of the fourteen K-means groupings was run through Esri's Tapestry Segmentation program, a geodemographic market segmentation system built from cluster analysis and data mining, to further assist in putting a metaphorical name and face to each of the groups (Esri 2019).

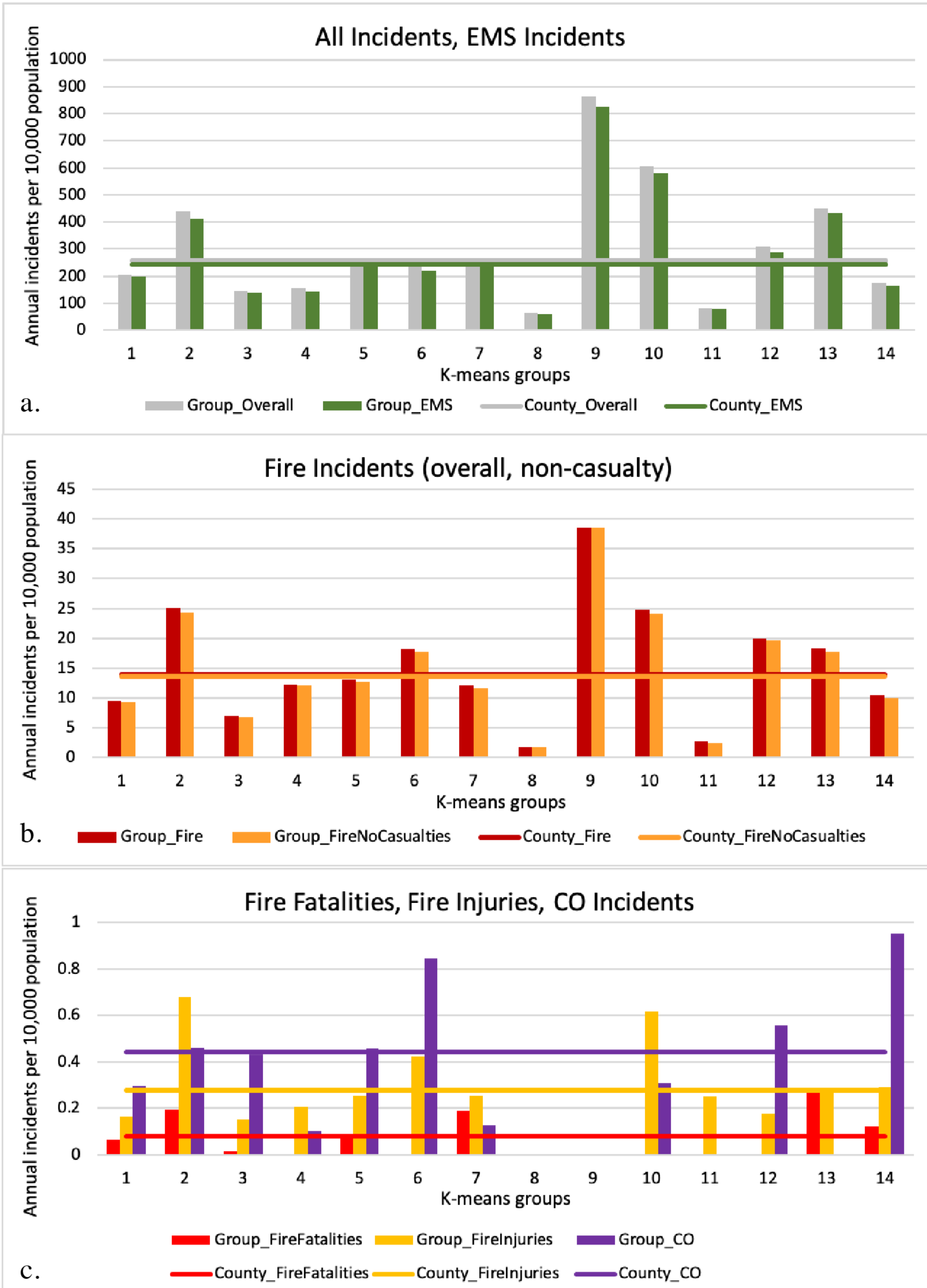

Figure 5.2: Incident Rates per person for each K-means group.
Subgraphs: a. Overall and EMS, b. Fire overall and non-casualty fires, c. Fire fatalities, fire injuries, and CO incidents

Groups 1, 3, 4, 8, and 11 all had consistently lower than average annual incident rates (per 10,000 people) for all types of incidents. This ranged from Group 8 with almost no calls to Group 1 with a slightly below average rate. Groups 8 and 11 both had very few block groups, and were primarily comprised of institutional areas, such as college dormitories, prisons, and parts of Fort Jackson. Both had less than half the average rate of incidents for all calls, EMS, all fire, and fire without casualties. Group 11 had a slightly below average rate for fire injuries. Group 8 had no fire injuries, and neither group had any fire fatalities or CO calls. Group 3 mostly had incident rates about half that of average, with CO rates right at the average. This group was primarily comprised of block groups in the northwestern and northeastern parts of the county. Its definitive feature was high Factor 4 values, and as an extension of that had high levels of alcohol and tobacco consumption. This was true both for total consumption amounts as were included in the best PCA results, as well as consumption per person or per household, which is important to note as these are also some of the faster growing (and thus largest) block groups in the county. Tapestry Segmentation also highlighted a significant population of younger families in this group. Group 4 had incidents rates primarily around half to three quarters of average. The exceptions were no fire fatalities and a very low rate of CO calls. It was primarily located south of downtown along the Congaree River, near the University of South Carolina. Many student apartment complexes are located in this neighborhood. It had higher than average Factor 6 values, and lower than average values for Factors 2, 5, and 9. These factors fit with the primarily college-aged fulltime student population identified in Tapestry Segmentation, which tends to be younger childless adults, with low income due to primarily being students rather than working fulltime. Group 1 was a primarily rural grouping (high Factor 3 values), located in northern Richland County and in the middle section of Lower Richland. It had slightly lower than average incidents rates for all types of calls.

Group 5 had average incident rates for all types of incidents. This group was comprised of a scattering of block groups around the periphery of the city of Columbia in primarily suburban neighborhoods with households headed by married couples. Its most prominent factors were higher than average values for Factor 2, and lower than average values for Factors 6 and 7. Group 2 had consistently higher than average values for all types of incidents. The most extreme of this was fire casualty (fatality and injury) rates of more than double the overall average. Group 2 is primarily located in northern Columbia, as well as a few block groups near the southern border of the city. It had some of the highest levels of Factor 1 in the study area, including having high rates for the risk variables with the greatest loadings for Factor 1.

Half the groups – Groups 6, 7, 9, 10, 12, 13, and 14 – did not have consistent incident rates as compared to the average, with some types of incidents having above average rates while others were below average. Group 6 comprises only three block groups, primarily residential. One is near the University of South Carolina, and the other two are located in the St Andrews area. This group is notable for its high Factor 8 values. It had no fire fatalities, EMS and overall incident rates slightly below average, overall fire and no casualty fire rates slightly above average, and fire injury and CO rates well above average. The primary risk variable in Factor 8 is poor English ability which could suggest that an inability to understand English-language warning materials might be related to the high rates of CO incidents. Group 7 contains about a dozen block groups scattered around the outskirts of Columbia. For most types of incidents this group had average rates, with the exceptions being a high rate of fire fatalities and low CO rates. High values for Factor 7 were the only notable factor. Group 9 is comprised of three block groups; the heart of downtown Columbia, the 5 Points neighborhood, and a residential area along I-77. It had high numbers of EMS and no casualty fire calls, but zero fire fatalities, injuries, or CO calls. Downtown and 5 Points are heavily commercial areas, that have a much larger daytime population than resident population, leading to higher overall numbers of incidents than would be expected based on the resident population. However, as most fire fatalities are residential (Ahrens 2017), it is reasonable to expect a lower than average rate of fatalities compared to overall calls. Factor 9 values were extremely high for this group, with no other factor values being noteworthy. Group 10 is comprised of four block groups, three in Lower Richland near the railroad tracks, and one on the north side of Columbia. Its somewhat rural setting is emphasized by both high Factor 3 values, as well as by the patterns identified in the Tapestry Segmentation data. Most of the incidents types (overall, EMS, all fires, no casualty fires, and fire injuries) had higher than average rates, with lower than average CO rates, and no fire fatalities. Group 12 is comprised of a few dozen block groups scattered around the more densely developed parts of the county, although outside the central core of Columbia. None of the factors had particularly high or low values, but the Tapestry Segmentation data identifies this group as being primarily younger single adults. This group in general had slightly above average incident rates, but with lower than average fire injuries, and no fire fatalities. Group 13 is located at the far end of Lower Richland, in one of the most rural areas of the county. This is emphasized by high Factor 3 values, as well as by the Tapestry Segmentation data. In particular this was one of the most prevalent areas for mobile homes. This group had slightly higher than average overall, EMS, overall fire, and no casualty fire rates, and no CO calls. The unusual aspect of incident rates was that fire injury and fatality rates were the same, as one of each occurred in this sparsely populated group. This meant an average injury rate, but more than twice the average fire fatality rate. Group 14 comprises a few dozen block groups located near the core of the county, particularly the city of Forest Acres and residential neighborhoods to the southeast of downtown Columbia. These are primarily white, well-educated neighborhoods, as seen by the low values of Factor 1 and in the Tapestry Segmentation data. This group had below average overall, EMS, overall fire, and no casualty fire incident rates, and average fire injury rates. However, this area also had above average fire fatality rates, and the highest CO rates of all fourteen groups.

5.2 Incidents per Battalion

Aggregation of incidents based on battalion boundaries provided additional insights into incident location. The battalions had drastically different rates of incidents (Table 5.1), and their boundaries did not align with the Local Moran's I or incident rate thematic map results. For example, the area containing the main EMS hot spot and all fire incidents hot spot is covered by two different battalions (Figure 5.3). Battalion 5 has a far higher than average rates of fire fatalities (Table 5.1). While one might think this is because of a single large hot spot within the battalion, overlaying battalion boundaries with fatalities shows instead two smaller hot spots on opposite sides of the battalion, plus a few standalone fatality incidents elsewhere in the battalion (Figure 5.4). As a comparison, in 2017 the state of South Carolina had a fire fatality rate of 17.3 per million people (0.173 per 10,000 people), compared to the national average of 11.2 per million people (0.112 per 10,000 people) (FEMA USFA 2019). Richland County as a whole and Battalions 1, 2, 3, and 4 all have fatality rates lower than the state and national average, whereas Battalion 5 has a higher than average fatality rate compared to the state or nation.

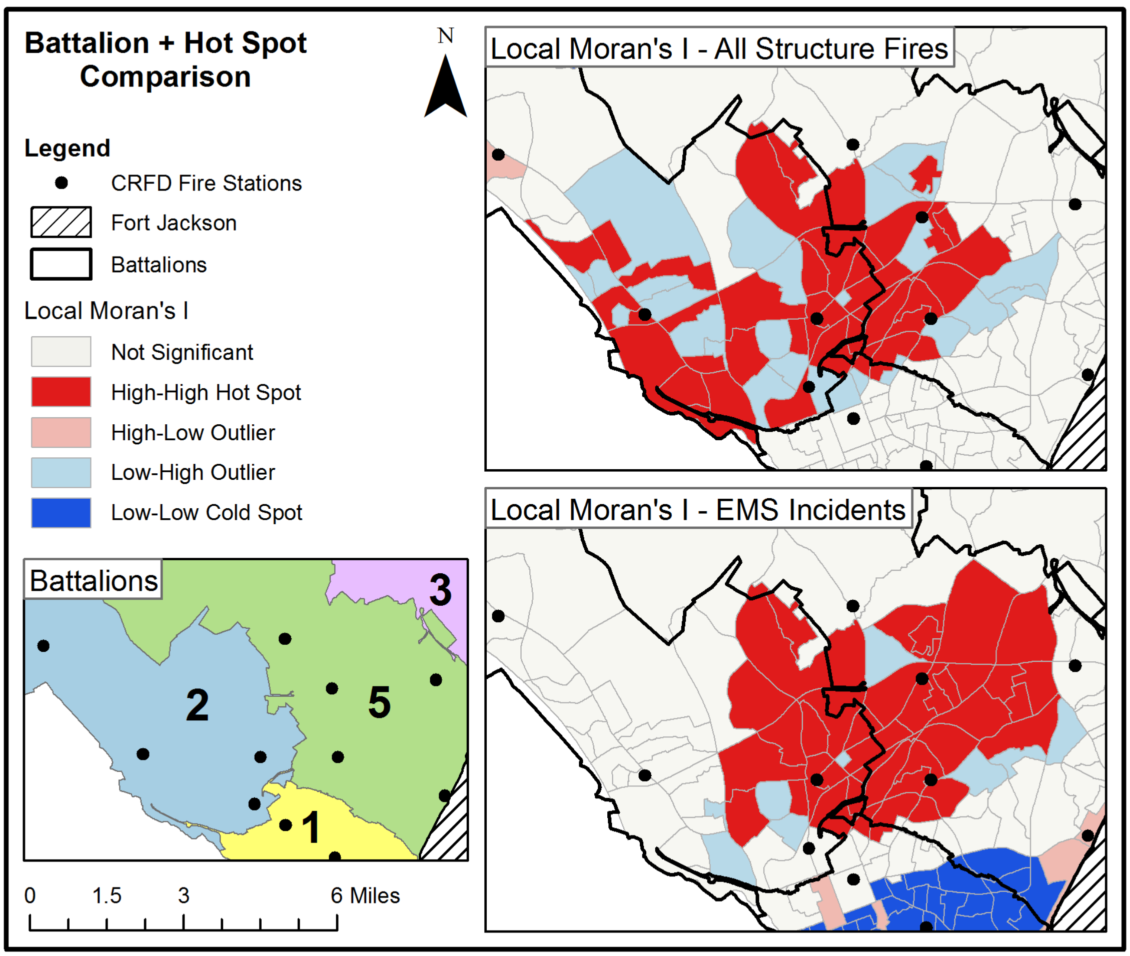

Figure 5.3: Comparison between battalion boundaries and the main EMS and fire incident hot spot

Table 5.1: Annual incident rates per 10,000 people by battalion and overall average

	Battalion 1	Battalion 2	Battalion 3	Battalion 4	Battalion 5	Average
All Incidents (EMS, CO, Fire)	163.63	274.61	182.60	331.94	371.20	256.69
EMS	149.74	259.43	172.38	314.92	352.64	242.26
CO	0.51	0.32	0.40	0.39	0.67	0.45
All Structure Fires	13.38	14.85	9.82	16.63	17.88	13.98
- Incidents with injuries	0.32	0.29	0.14	0.28	0.45	0.28
- Civilian injuries	0.39	0.40	0.15	0.30	0.47	0.33
- Incidents with fatalities	0.10	0.04	0.00	0.11	0.20	0.08
- Civilian fatalities	0.10	0.04	0.00	0.11	0.22	0.08
- No Casualties	12.96	14.52	9.68	16.28	17.23	13.63

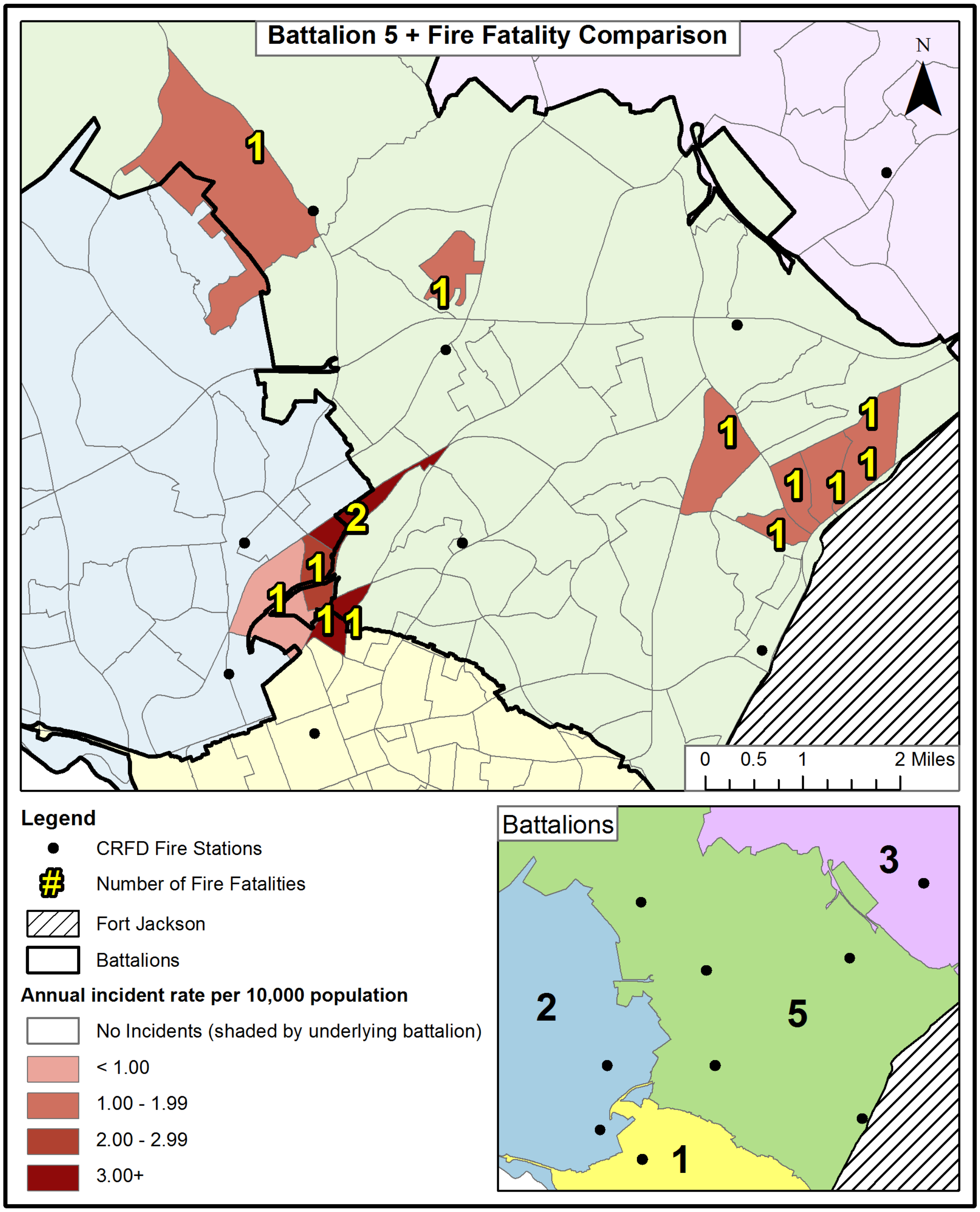

Figure 5.4: Comparison of fire fatality locations within and near Battalion 5

5.3 Limitations and Additional Considerations

Three additional areas of limitations within this work consist of some challenges with ecological fallacies related to the unit of analysis, limitations of the data in the NFIRS reports, and challenges highlighted by a working knowledge of day to day operations within the fire service. These limitations are presented in hopes to give some perspective on the results and conclusions, and to provide opportunities to strengthen any further additional analysis.

5.3.1 Ecological Fallacy

An ecological fallacy is a statistical fallacy where inferences are made about individuals based on analysis of a group to which they belong. In this case, making conclusions about individuals based on analysis of Census data, which is an aggregate of individuals. All of the types of incidents studied here are individual in nature. They start in a single building or involve a single medical patient. Even in larger fire or CO incidents where large numbers of people may eventually be displaced or otherwise involved, the incident still started at a specific location; it did not start all over a neighborhood all at the same time. The analysis presented in this work aggregated multiple incidents up to the block group level, running analysis that used block group level incident rates, rather than examining the characteristics of individual incidents. This analysis of incidents as well as demographic and behavioral traits that are all individual in nature but analyzed at an aggregate level is an example of an ecological fallacy. However, since Census data is not available at the individual or household level it is a somewhat unavoidable ecological fallacy. While correlations have been made between certain risk factors and incident types, it isn't known whether or not the individuals involved in the incident shared these same risk traits with the rest of their block group. Similarly, PCA factors were based on the block group as a whole, but the specific risk variables may not group together in the same way for individuals. This same ecological fallacy continues on when PCA factors are used in cluster analysis.

Some of the data required to check individual incidents against block groups could potentially be found in NFIRS reports. For example, building type and age and gender of any fire victims should appear in most reports, whereas other risk factors such as the presence of unattended children might at best appear in the incident narrative at the discretion of whoever wrote the report. Future analysis could dig further into the data available in the NFIRS reports and assess to what extent the individuals involved in a block group's incidents are representative of the area as a whole. The use of the smallest possible unit of analysis, in this case the block group, should have helped to minimize although not entirely correct for the potential differences in correlation between the areal unit (i.e., block group) and individuals (Openshaw 1984).

5.3.2 NFIRS Limitations

As previously described, the NFIRS reports hold significantly more data points than were used in this analysis. However, like with any dataset they are not perfect, and the reports do not capture all possible information about all of the incidents. Limitations of NFIRS reports can be divided into two main areas; first, issues with data quality and accuracy, and second, issues with how the incidents were counted. Awareness of these limitations comes from both reviewing the NFIRS reports, as well as from experience assisting with writing these reports as part of working as a firefighter.

Issues of data quality are related to the complexity of the NFIRS report form and who fills out the report when. NFIRS reports are complex, with dozens of required boxes to fill in addition to an open narrative space. Depending on who writes the report (usually the incident commander), and how carefully and thoroughly they complete it, NFIRS reports can be a goldmine of risk-related information. Some of these details are in required boxes, such as the age and gender of any civilian injuries or fatalities, whereas other details may only appear in the narrative of a particularly thorough report. For example, noting that a homeowner involved in a kitchen fire appeared to be intoxicated and stated they forgot about a pan on the stove, or noting that a child who was playing with matches appeared to have little or no supervision. It is important to consider that these reports represent a snapshot in time and reflect who wrote them. One incident commander might write a single sentence narrative for a medical call stating only "Engine company assisted EMS," whereas another incident commander might right a paragraph including details about where the patient was found, what their medical complaints and condition were, and what type of care was provided by which responders. Similarly, a structure fire narrative might be a paragraph or one or more pages, depending on the complexity of the incident. As a snapshot in time, reports reflect what is known in the moment. A victim may be listed as a fire injury in the associated NFIRS report but listed as a fatality by the State Fire Marshal's Office because they left the scene alive but days, weeks, or months later succumbed to their injuries.

Issues with data quality can also be due to incomplete or missing reports. Federally NFIRS is a voluntary program, although many departments including CRFD require their incident reports be submitted to the NFIRS program. Sometimes reports don't happen, whether due to technical issues, negligence, or forgetfulness. Reports may also be partially completed, such as the age of fire fatality being unknown. Or a street address may get mistyped, leading to problems geocoding the incident. Address issues leads into the second area of NFIRS limitations – how the incidents are counted.

Every incident is tied to a location. In the case of a house fire it is clear to see how this might be related to large neighborhood trends. However, some incidents occur at relatively random locations. For example, if a person has a stroke while in a moving vehicle, the block group the incident gets recorded in has more to do with what time they started driving and how many traffic lights they hit than it does with the individual's community. For this reason, some medical calls may have very little to do with the block group in which they occur. Another issue with how incidents are counted is whether or not separate reports are created for exposures (i.e. neighboring buildings or apartment units). If separate incident reports are created for each property involved, then a house fire that destroys one house and melts the siding on the neighboring two houses might suddenly appear as if three separate structure fires occurred on that block, despite all damage originating from a single initial point of ignition.

5.3.3 Considerations based on professional fire service experience

Hands on experience in the fire service was valuable for multiple aspects of this research, but also provided some inherent bias to the analysis. First, in reviewing the existing literature, fire service experience was helpful in understanding the strengths and weaknesses of previous risk assessment methodologies. Second, it was helpful in understanding the risk variable literature, such as why a specific trait might place a person or building at increased risk. Third, fire service experience was helpful in analyzing the results, spotting patterns, and making connections between research results and anecdotal knowledge of CRFD incidents.

When reviewing the history of fire risk assessment methods, fire service experience was valuable in evaluating the strengths and weakness inherent to different methodologies. For example, a strength of the early paper fire insurance maps is the detail they provide about building construction and occupancy. These are reoccurring topics throughout firefighter training because of how important they are in determining the spread of fire throughout a building, how long a building can burn before it is likely to collapse, and who and what might be at risk inside the building. In contrast, the mid-twentieth century mathematical models of fire risk focused entirely on distance to the nearest fire engine, almost completely ignoring who or what was at risk. While shortsighted about building construction and occupancy, response time is an important factor. Fire can spread very quickly, especially if a heavy fuel load (e.g., flammable liquids, lots of synthetic materials) or certain types of building constructions methods (e.g., lightweight trusses, numerous void spaces) are involved, and it is much easier to stop a small fire than a large one. Quick notification of the fire service and quick response are key to stopping fires when they are small. A quick response can be equally important for some types of medical calls, such as when CPR or hemorrhage control is involved, where a quick response might mean a life saved. The importance of a quick response also highlighted how delays caused by a fire engine being stopped by a train can have a potentially deleterious outcome for the incident. Comprehensive risk assessments that consider a combination of risk factors leads to understanding why a specific trait might be a risk factor.

Fire service experience was helpful in understanding risk factors by providing knowledge of how fires start and spread through buildings, how unintentional CO poisoning might occur, and understanding how personal traits (e.g., demographic, behavioral) might influence risk related to medical and fire incidents. Some of this has already been touched upon in Section 2.2, with the basic connections made between specific risk variables and their potential for increased likelihood of ignition, faster fire spread, and/or potential to prevent a timely escape from a fire. However, there is a difference between reading about the risk of inadvertent ignition posed by improper disposable of smoking materials and having the experience of extinguishing melting house siding set alight by a cigarette which escaped from an ash can. Anyone can read that overloaded electrical wiring might place an older house at risk of a fire, but training as a firefighter makes one aware that building age can also influence how the structure was built (construction materials and techniques), as well as the likelihood that multiple renovations over the decades may have left void spaces in which fire can hide or travel quickly unchecked. Such changes can also alter the interior layout in such a way that escape from a fire could prove challenging. Perhaps most visceral of all, the experience of actually being in a structure fire – feeling the overwhelming heat, being wrapped in smoke so thick you are unable to see your hand extended in front of you, knowing from experience how debilitating even minor smoke inhalation can be – provides a unique perspective on the challenges of escaping a fire. For example, understanding why moving slowly or an inability to crawl might make an elderly person less likely to be able to escape a fire than a young adult.

Finally, fire service experience was helpful in analyzing and providing context to the results. It helped highlight certain patterns and make connections between research results and anecdotal knowledge of CRFD incidents. An understanding of why a certain trait might be a risk factor is beneficial in understanding why specific risk variables were grouped together in the PCA results. One example was Factor 1 (Systematic Hard Times), which highlights the socioeconomic aspects of fire risk discussed in Section 2.2.4. K-means Group 2 had high rates of Factor 1, partially overlapped with the main fire and EMS hot spots, and aligned with anecdotal evidence from CRFD personnel about which parts of the county had the greatest number of incidents. While individual variables and factors can be mapped, a working knowledge of CRFD operations was helpful in making connections between these maps and ongoing CRFD incidents and radio traffic. For example, for a period of several weeks coinciding with writing up the results of this thesis, a number of structure fires occurred in the far part of Lower Richland. Knowledge that this part of the county had high values for Factor 4 (Rural), comprised of both significant distance to nearest apparatus and high rates of mobile home ownership, meant that it was unsurprising to hear in the radio traffic that a number of these fires occurred in mobile homes, and that the water supply was provided via tanker truck shuttle instead of nearby hydrants. While this working knowledge was helpful in confirming patterns in the results, there is also the potential that it introduced some confirmation bias, making previously suspected patterns appear more visible than they might otherwise to an outsider. Overall, fire service experience was highly beneficial in achieving a comprehensive understanding of risk factors, risk assessment methods, and the results of this assessment. For these reasons, while the possibility for experiential confirmation bias is acknowledged, it is far outweighed by the positive benefits brought to this work by previous fire service experience.

CHAPTER 6

CONCLUSION

The combination of geospatial and statistical methods used in this work were able to answer the two research questions. Research Question 1 asked what is the spatial variability of structure fires, carbon monoxide incidents, and emergency medical calls in Richland County, SC? These incident types can be further divided into seven types; all incidents combined, all structure fires, structure fires resulting in civilian (as opposed to fire service) fatality, structure fires resulting in civilian injury, structure fires with no casualties (i.e., no fatalities or injuries), emergency medical calls, and carbon monoxide calls. Local Moran's I and thematic mapping of incident rates were used to answer Research Question 1. Research Question 2 asked how the underlying community variations in physical and social risk factors correlate with each other and with the types of emergency calls described in Research Question 1. PCA, K-means, and correlation analysis were used to answer Research Question 2.

The most useful methods proved to be PCA combined with K-means for identifying which risk factors shared similar patterns that could be combined into related factors, and then clustering block groups based on similar combinations of factors. Local Moran's I proved useful in identifying hot and cold spots of incident types that had a large volume of incidents. It was less useful with incident types with a small number of incidents, and the additional information provided by thematic mapping of incident rates was necessary to form a complete picture of incident distribution. Correlation analysis proved to be of limited value, as it was only able to provide a basic yes or no of statistical significance between individual variables and incidents across the county as a whole, as opposed to the more nuanced perspective provided by PCA and K-means. Correlation analysis between PCA output and incident types was slightly more helpful in identifying which PCA factors were most strongly related to each incident type.

Local Moran's I and thematic mapping of incident rates identified northern Columbia and Lower Richland as the places with the highest incident rates for EMS incidents and structure fires. Hot spots of fire fatalities, fire injuries, and CO incidents were harder to identify due to their more sporadic nature (i.e., many block groups did not have one or more of these types of incidents). For these three types of calls thematic mapping of incident rates and considering calls by battalion boundaries proved more useful, with Battalion 5 having the highest rate of fire fatalities and injuries. These casualties were spread over multiple neighborhoods within Battalion 5, with some of these neighborhoods crossing into other battalions.

PCA reduced the over thirty risk factors into nine principal factors. The factors explaining the most variance related to systematic hard times (positive loadings for Black, Medicaid/care Insurance, Single Parents, No Diploma, No Insurance, and Disabled, and negative loading for White), older home owners (positive loadings for One/Two Family House, Over 50, Owner Occupied, Disabled, and Postwar House and negative loadings for Multi Family homes), and rural location (positive loadings for Water Supply, Mobile Home, Ladder Distance, and Engine Distance). K-means was then used to cluster these factors, resulting in fourteen different groupings of block groups that each shared similar patterns of risk factors. One of these groupings, strongly related to high values of PCA Factor 1 (Systematic Hard Times), had significant overlap with the main hot spots of fire and EMS incidents.

A few limitations and other pieces of perspective on this analysis should be noted. First, there are ecological fallacy concerns resulting from aggregating individual incidents to the block group level. Use of the smallest possible Census region available (e.g., block group) should help to mitigate these issues, but they are somewhat unavoidable due to the lack of publicly available household level Census data and only so many demographic variables being recorded in NFIRS reports. Another consideration is that while NFIRS is one of the most comprehensive sources of data about fire service incidents, the reports can still have a wide range of issues with data accuracy and how incidents are reported. Finally, while experience working in fire service operations provided a significant benefit in understanding the literature and comprehending the results, it did introduce the potential for confirmation bias, in that some patterns of results may have been more prominent than they otherwise would have been.

Next steps for this research fall into two main areas. First, applying the findings of this work to ongoing CRFD prevention and operations work. Second, investigating deeper into the data contained within the NFIRS reports. While the results of this research align with anecdotal statements made by members of CRFD as to the regions with highest call volume, it is important to have quantitative data to back up these statements. It is also important to look for previously unidentified patterns of risk that might lead to opportunities for increased risk reduction work. For example, K-means Group 6 highlighted regions with larger than average Asian populations and many residents with limited English ability and high rates. Perhaps consideration should be given to what languages CRFD is publishing risk reduction materials in. Consideration can also be given to the need for targeted risk reduction campaigns in specific neighborhoods based on key risk factors characteristic of those neighborhoods.

Investigating deeper into the data could include looking at the risk factors found in specific incidents, such as the type of structure involved or a victims age or race. While the literature and block group level analysis may suggest that a specific risk factor was likely involved with a certain fire fatality or injury, it would be worth checking the actual incident record to confirm this. This level of analysis depth could confirm or deny the patterns suggested by block group level correlations between incident rates and risk factors. Another form of digging deeper into the EMS data would be to do a more comprehensive medical incident risk assessment by collaborating in Richland EMS, and looking at all medical calls in the county, not just those acute enough for CRFD to respond to them.

Finally, it should be recognized that risk assessments capture a moment in time. As neighborhoods grow, shrink, or change in composition the risk associated with these areas may change. The relative risk across the county may also shift. Similarly risk reduction work done on one topic or type of incident may reduce incidents enough to highlight a different type of incident still in need of work. Therefore, risk assessments need to be redone on a regular basis. This could be still at a block group level in a few years, but the 2020 Census data could also be used to do analysis at a finer spatial scale (i.e., block level). This research has tested methodology, identified areas and risk variables of interest, and builds a footing for future updates to this assessment.

REFERENCES

Ahrens, Marty. 2017. “Trends and Patterns of U.S. Fire Loss.” Research. Quincy, MA: National Fire Protection Association (NFPA). https://www.nfpa.org/-/media/Files/News-and-Research/Fire-statistics-and-reports/US-Fire-Problem/osTrends.pdf.

Aksha, Sanam K., Luke Juran, Lynn M. Resler, and Yang Zhang. 2019. “An Analysis of Social Vulnerability to Natural Hazards in Nepal Using a Modified Social Vulnerability Index.” *International Journal of Disaster Risk Science* 10 (1): 103–16. https://doi.org/10.1007/s13753-018-0192-7.

Amdahl, Gary. 2001. *Disaster Response: GIS for Public Safety*. Redlands, CA: ESRI Press.

Anselin, Luc. 1995. “Local Indicators of Spatial Association-LISA.” *Geographical Analysis* 27 (2): 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x.

Badri, Masood A., Amr K. Mortagy, and Colonel Ali Alsayed. 1998. “A Multi-Objective Model for Locating Fire Stations.” *European Journal of Operational Research* 110 (2): 243–60. https://doi.org/10.1016/S0377-2217(97)00247-6.

Baker, Earl J., and Joe Gordon McPhee. 1975. *Land Use Management and Regulation in Hazardous Areas: A Research Assessment*. Program on Technology, Environment and Man, #NSF-RA-E-75-008. Boulder, CO: University of Colorado, Institute for Behavioral Science.

Barták, Vojtěch, Kateřina Gdulová, Olga Špatenková, Aleš Bárta, and Petra Šímová. 2014. “Modelling the Probability of Building Fires.” *Geoinformatics FCE CTU* 13 (0): 37–48. https://doi.org/10.14311/gi.13.5.

Blackwell, Thomas H., and Jay S. Kaufman. 2002. “Response Time Effectiveness: Comparison of Response Time and Survival in an Urban Emergency Medical Services System.” *Academic Emergency Medicine* 9 (4): 288–95. https://doi.org/10.1197/aemj.9.4.288.

Boruff, Bryan J., Christopher Emrich, and Susan L. Cutter. 2005. “Erosion Hazard Vulnerability of US Coastal Counties.” *Journal of Coastal Research* 215 (September): 932–42. https://doi.org/10.2112/04-0172.1.

Çatay, Bülent. 2011. “Siting New Fire Stations in Istanbul: A Risk-Based Optimization Approach.” *OR Insight* 24 (2): 77–89. https://doi.org/10.1057/ori.2011.3.

Centers for Disease Control and Prevention (CDC). 1997. “Use of Unvented Residential Heating Appliances -- United States, 1988-1994.” *MMWR Morbitiy Mortality Weekly Report* 46 (51): 1221–24.

Chakraborty, Jayajit, Graham A. Tobin, and Burrell E. Montz. 2005. “Population Evacuation: Assessing Spatial Variability in Geophysical Risk and Social Vulnerability to Natural Hazards.” *Natural Hazards Review* 6 (1): 23–33. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:1(23).

Chevalier, Philippe, Isabelle Thomas, David Geraets, Els Goetghebeur, Olivier Janssens, Dominique Peeters, and Frank Plastria. 2012. “Locating Fire Stations: An Integrated Approach for Belgium.” *Socio-Economic Planning Sciences* 46 (2): 173–82. https://doi.org/10.1016/j.seps.2012.02.003.

Chou, Yue Hong. 1992. “Management of Wildfires with a Geographical Information System.” *International Journal of Geographical Information Systems* 6 (2): 123–40. https://doi.org/10.1080/02693799208901900.

Clark, Andrew, Jessica Smith, and Carole Conroy. 2015. “Domestic Fire Risk: A Narrative Review of Social Science Literature and Implications for Further Research.” *Journal of Risk Research* 18 (9): 1113–29. https://doi.org/10.1080/13669877.2014.913660.

Columbia Fire Department. 2019. “Columbia Fire Department.” Governmental page. 2019. www.colafire.net.

Cone, David C., Nicholas Galante, and Donald S. MacMillan. 2008. “Can Emergency Medical Dispatch Systems Safely Reduce First-Responder Call Volume?” *Prehospital Emergency Care* 12 (4): 479–85. https://doi.org/10.1080/10903120802290844.

Corcoran, Jonathan, Gary Higgs, and Angela Higginson. 2011. “Fire Incidence in Metropolitan Areas: A Comparative Study of Brisbane (Australia) and Cardiff (United Kingdom).” *Applied Geography* 31 (1): 65–75. https://doi.org/10.1016/j.apgeog.2010.02.003.

Cova, Tom J. 1999. “GIS in Emergency Management.” In *Geographic Information Systems: Principles, Techniques, Applications, and Management*, edited by P.A. Longley, Michael F. Goodchild, D.J. Maguire, and D.W. Rhind, 845–58. New York, NY: John Wiley & Sons.

Cutter, Susan L., Bryan J. Boruff, and W. Lynn Shirley. 2003. "Social Vulnerability to Environmental Hazards." *Social Science Quarterly* 84 (2): 242–61. https://doi.org/10.1111/1540-6237.8402002.

Cutter, Susan L., Jerry T. Mitchell, and Michael S. Scott. 2000. "Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina." *Annals of the Association of American Geographers* 90 (4): 713–37. https://doi.org/10.1111/0004-5608.00219.

Davis, Corey S., Sarah Ruiz, Patrick Glynn, Gerald Picariello, and Alexander Y. Walley. 2014. "Expanded Access to Naloxone Among Firefighters, Police Officers, and Emergency Medical Technicians in Massachusetts." *American Journal of Public Health* 104 (8): e7–9. https://doi.org/10.2105/AJPH.2014.302062.

Duncanson, Mavis, Alistair Woodward, and Papaarangi Reid. 2002. "Socioeconomic Deprivation and Fatal Unintentional Domestic Fire Incidents in New Zealand 1993–1998." *Fire Safety Journal* 37 (2): 165–79. https://doi.org/10.1016/S0379-7112(01)00033-9.

Ebert, Annemarie, Norman Kerle, and Alfred Stein. 2009. "Urban Social Vulnerability Assessment with Physical Proxies and Spatial Metrics Derived from Air- and Spaceborne Imagery and GIS Data." *Natural Hazards* 48 (2): 275–94. https://doi.org/10.1007/s11069-008-9264-0.

Emmi, Philip C., and Carl A. Horton. 1995. "A Monte Carlo Simulation of Error Propagation in a GIS-Based Assessment of Seismic Risk." *International Journal of Geographical Information Systems* 9 (4): 447–61. https://doi.org/10.1080/02693799508902049.

Esri. 2019. "2019 Tapestry Segmentation Methodology." Redlands, CA. https://downloads.esri.com/esri_content_doc/dbl/us/J9941_Tapestry_Segmentation_Methodology_2019.pdf.

Federal Emergency Management Agency, United States Fire Administration, National Fire Data Center. 1997. "Socioeconomic Factors and the Incidence of Fire." Governmental FA 170. Emmitsburg, MD: Federal Emergency Management Agency, United States Fire Administration, National Fire Data Center. https://www.usfa.fema.gov/downloads/pdf/statistics/socio.pdf.

———. 2018. "Fire Risk in 2016." *Topical Fire Report Series* 19 (6): 17.

———. 2019. "Fire in the United States 2008-2017." Federal Emergency Management Agency, United States Fire Administration, National Fire Data Center. https://www.usfa.fema.gov/downloads/pdf/publications/fius20th.pdf.

Flood, Joe. 2010. *The Fires: How a Computer Formula Burned down New York City - and Determined the Future of American Cities*. New York, NY: Riverhead Books.

Friedman, Don G. 1975. *Computer Simulation in Natural Hazard Assessment*. Program on Technology, Environment and Man, NSF-RA-E-75-002. Boulder, CO: University of Colorado, Institute for Behavioral Science. https://nehrpsearch.nist.gov/static/files/NSF/PB261755.pdf.

Gee, Thomas H. 2007. "Establishment of a Communitywide EMS First-Responder Program:" *Journal of Healthcare Management* 52 (3): 206–10. https://doi.org/10.1097/00115514-200705000-00011.

Green, Linda V., and Peter J. Kolesar. 2004. “Anniversary Article: Improving Emergency Responsiveness with Management Science.” *Management Science* 50 (8): 1001–14. https://doi.org/10.1287/mnsc.1040.0253.

Hampson, Neil B., Christine C Kramer, Richard G Dunford, and Diane M Norkool. 1994. “Carbon Monoxide Poisoning From Indoor Burning of Charcoal Briquets.” *JAMA* 271 (1): 52–53. https://doi.org/10.1001/jama.1994.03510250068037.

Hampson, Neil B., and A L Stock. 2006. “Storm-Related Carbon Monoxide Poisoning: Lessons Learned from Recent Epidemics.” *Undersea and Hyperbaric Medicine* 33 (4): 257–63.

Hart, Darrick Lamont. 2000. “Overcoming the Flames of Prejudice : The Intergration [Sic] of the Columbia Fire Department, Columbia, South Carolina, 1948-1969.” Master’s, Columbia, SC: University of South Carolina.

Harvey, Pauline A, Jeffrey J Sacks, George W Ryan, and Patricia F Bender. 1998. “Residential Smoke Alarms and Fire Escape Plans.” *Public Health Reports* 113 (5): 459–64.

Hensler, Bruce. 2011. *Crucible of Fire: Nineteenth-Century Urban Fires and the Making of the Modern Fire Service*. Vol. 1st ed. Washington, D.C.: Potomac Books. https://login.pallas2.tcl.sc.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=e000xna&AN=388823&site=ehost-live.

Higgins, E., M. Taylor, M. Jones, and P.J.G. Lisboa. 2013. “Understanding Community Fire Risk—A Spatial Model for Targeting Fire Prevention Activities.” *Fire Safety Journal* 62 (November): 20–29. https://doi.org/10.1016/j.firesaf.2013.02.006.

Hogg, Jane M. 1968. “The Siting of Fire Stations.” *Journal of the Operational Research Society* 19 (3): 275–87. https://doi.org/10.1057/jors.1968.71.

Holborn, P.G, P.F Nolan, and J Golt. 2003. “An Analysis of Fatal Unintentional Dwelling Fires Investigated by London Fire Brigade between 1996 and 2000.” *Fire Safety Journal* 38 (1): 1–42. https://doi.org/10.1016/S0379-7112(02)00049-8.

Iqbal, Shahed, Jacquelyn H. Clower, Michael King, Jeneita Bell, and Fuyuen Y. Yip. 2012. “National Carbon Monoxide Poisoning Surveillance Framework and Recent Estimates.” *Public Health Reports* 127 (5): 486–96. https://doi.org/10.1177/003335491212700504.

Jansen, John D. 2005. *Going to Blazes: A 200-Year Illustrated History of the Columbia, South Carolina, Fire and Rescue Service*. Evansville, IN: M.T. Publishing.

Jennings, Charles R. 1999. “Socioeconomic Characteristics and Their Relationship to Fire Incidence: A Review of the Literature.” *Fire Technology* 35 (1): 7–34. https://doi.org/10.1023/A:1015330931387.

Jennings, Charles R. 2013. “Social and Economic Characteristics as Determinants of Residential Fire Risk in Urban Neighborhoods: A Review of the Literature.” *Fire Safety Journal* 62 (A): 13–19. https://doi.org/10.1016/j.firesaf.2013.07.002.

Jonsson, Anders, Carl Bonander, Finn Nilson, and Fredrik Huss. 2017. “The State of the Residential Fire Fatality Problem in Sweden: Epidemiology, Risk Factors, and Event Typologies.” *Journal of Safety Research* 62 (September): 89–100. https://doi.org/10.1016/j.jsr.2017.06.008.

Kellermann, Arthur L, Bela B Hackman, Grant Somes, Lindacarol Nail, and Perry Dobyns. 1993. “Impact of First-Responder Defibrillation in an Urban Emergency

Medical Services System.” *JAMA* 270 (14): 1708–13. https://doi.org/10.1001/jama.1993.03510140068031.

King, David Richard, Andreas Larentzakis, and Elie P. Ramly. 2015. “Tourniquet Use at the Boston Marathon Bombing: Lost in Translation.” *Journal of Trauma and Acute Care Surgery* 78 (3): 594–99. https://doi.org/10.1097/TA.0000000000000561.

Kue, Ricky C., Elizabeth S. Temin, Scott G. Weiner, Jonathan Gates, Melissa H. Coleman, Jonathan Fisher, and Sophia Dyer. 2015. “Tourniquet Use in a Civilian Emergency Medical Services Setting: A Descriptive Analysis of the Boston EMS Experience.” *Prehospital Emergency Care* 19 (3): 399–404. https://doi.org/10.3109/10903127.2014.995842.

Le Baudour, Chris, J. David Bergeron, and Keith Wesley. 2019. *Emergency Medical Responder: First on Scene*. 11th ed. London: Pearson.

Lessing, Peter, Charles P. Messina, and Robert F. Fonner. 1983. “Landslide Risk Assessment.” *Environmental Geology* 5 (2): 93–99.

Lin, Yuan-Shang. 2004. “Life Risk Analysis in Residential Building Fires.” *Journal of Fire Sciences* 22 (6): 491–504. https://doi.org/10.1177/0734904104043030.

Liu, Nan, Bo Huang, and Magesh Chandramouli. 2006. “Optimal Siting of Fire Stations Using GIS and ANT Algorithm.” *Journal of Computing in Civil Engineering* 20 (5): 361–69. https://doi.org/10.1061/(ASCE)0887-3801(2006)20:5(361).

Malta Hansen, Carolina, Kristian Kragholm, David A. Pearson, Clark Tyson, Lisa Monk, Brent Myers, Darrell Nelson, et al. 2015. “Association of Bystander and First-Responder Intervention With Survival After Out-of-Hospital Cardiac Arrest in

North Carolina, 2010-2013.” *JAMA* 314 (3): 255. https://doi.org/10.1001/jama.2015.7938.

Meisel, Zachary F., Jesse M. Pines, Daniel Polsky, Joshua P. Metlay, Mark D. Neuman, and Charles C. Branas. 2011. “Variations in Ambulance Use in the United States: The Role of Health Insurance: HEALTH INSURANCE AND AMBULANCE USE.” *Academic Emergency Medicine* 18 (10): 1036–44. https://doi.org/10.1111/j.1553-2712.2011.01163.x.

Murray, Alan T. 2013. “Optimising the Spatial Location of Urban Fire Stations.” *Fire Safety Journal* 62 (Part A): 64–71. https://doi.org/10.1016/j.firesaf.2013.03.002.

Newgard, Craig D., Robert H. Schmicker, Jerris R. Hedges, John P. Trickett, Daniel P. Davis, Eileen M. Bulger, Tom P. Aufderheide, et al. 2010. “Emergency Medical Services Intervals and Survival in Trauma: Assessment of the ‘Golden Hour’ in a North American Prospective Cohort.” *Annals of Emergency Medicine* 55 (3): 235-246.e4. https://doi.org/10.1016/j.annemergmed.2009.07.024.

NOAA National Centers for Environmental Information (NCEI). 2020. “U.S. Billion-Dollar Weather and Climate Disasters.” 2020. https://www.ncdc.noaa.gov/billions/.

Openshaw, Stan. 1984. “Ecological Fallacies and the Analysis of Areal Census Data.” *Environment and Planning A: Economy and Space* 16 (1): 17–31. https://doi.org/10.1068/a160017.

Oswald, Diane. 1997. *Fire Insurance Maps: Their History and Applications*. College Station, Texas: Lacewing Press.

Park, Peter Y., Wook Rak Jung, Godfred Yeboah, Garreth Rempel, Dan Paulsen, and Dave Rumpel. 2016. “First Responders’ Response Area and Response Time Analysis with/without Grade Crossing Monitoring System.” *Fire Safety Journal* 79 (January): 100–110. https://doi.org/10.1016/j.firesaf.2015.11.003.

Plane, Donald R., and Thomas E. Hendrick. 1977. “Mathematical Programming and the Location of Fire Companies for the Denver Fire Department.” *Operations Research* 25 (4): 563–78. https://doi.org/10.1287/opre.25.4.563.

Pons, Peter T, and Vincent J Markovchick. 2002. “Eight Minutes or Less: Does the Ambulance Response Time Guideline Impact Trauma Patient Outcome?” *The Journal of Emergency Medicine* 23 (1): 43–48. https://doi.org/10.1016/S0736-4679(02)00460-2.

ReVelle, Charles. 1991. “Siting Ambulances and Fire Companies: New Tools for Planners.” *Journal of the American Planning Association* 57 (4): 471–84. https://doi.org/10.1080/01944369108975521.

Ristow, Walter W. 1981. “Sanborn Maps: Introduction to the Collection.” In *Fire Insurance Maps in the Library of Congress : Plans of North American Cities and Towns Produced by the Sanborn Map Company : A Checklist*, 773. Washington, D.C.: Library of Congress. https://lccn.loc.gov/80607938.

Rogers, Frederick B., Katelyn J. Rittenhouse, and Brian W. Gross. 2015. “The Golden Hour in Trauma: Dogma or Medical Folklore?” *Injury* 46 (4): 525–27. https://doi.org/10.1016/j.injury.2014.08.043.

Rucker, Donald W, Roger A Edwards, Helen R Burstin, Anne C O’Neil, and Troyen A Brennan. 1997. “Patient-Specific Predictors of Ambulance Use.” *Annals of*

Emergency Medicine 29 (4): 484–91. https://doi.org/10.1016/S0196-0644(97)70221-X.

Runefors, Marcus, Nils Johansson, and Patrick van Hees. 2017. “The Effectiveness of Specific Fire Prevention Measures for Different Population Groups.” *Fire Safety Journal* 91 (July): 1044–50. https://doi.org/10.1016/j.firesaf.2017.03.064.

Runyan, Carol W., Shrikant I. Bangdiwala, Mary A. Linzer, Jeffrey J. Sacks, and John Butts. 1992. “Risk Factors for Fatal Residential Fires.” *New England Journal of Medicine* 327: 859–63. https://doi.org/10.1056/NEJM199209173271207.

Scerbo, Michelle H., John B. Holcomb, Ethan Taub, Keith Gates, Joseph D. Love, Charles E. Wade, and Bryan A. Cotton. 2017. “The Trauma Center Is Too Late: Major Limb Trauma without a Pre-Hospital Tourniquet Has Increased Death from Hemorrhagic Shock.” *Journal of Trauma and Acute Care Surgery* 83 (6): 1165–72. https://doi.org/10.1097/TA.0000000000001666.

Schachterle, Stephen E, David Bishai, Wendy Shields, Rebecca Stepnitz, and Andrea C Gielen. 2012. “Proximity to Vacant Buildings Is Associated with Increased Fire Risk in Baltimore, Maryland, Homes.” *Injury Prevention* 18 (2): 98–102. https://doi.org/10.1136/injuryprev-2011-040022.

Schilling, David A., Charles Revelle, Jared Cohon, and D.Jack Elzinga. 1980. “Some Models for Fire Protection Locational Decisions.” *European Journal of Operational Research* 5 (1): 1–7. https://doi.org/10.1016/0377-2217(80)90067-3.

Schreuder, J.A.M. 1981. “Application of a Location Model to Fire Stations in Rotterdam.” *European Journal of Operational Research* 6 (2): 212–19. https://doi.org/10.1016/0377-2217(81)90210-1.

Shai, Donna. 2006. “Income, Housing, and Fire Injuries: A Census Tract Analysis.” *Public Health Reports* 121 (2): 149–54. https://doi.org/10.1177/003335490612100208.

Shai, Donna, and Paul Lupinacci. 2003. “Fire Fatalities among Children: An Analysis across Philadelphia’s Census Tracts.” *Public Health Reports* 118 (2): 115–26. https://doi.org/10.1093/phr/118.2.115.

Shu-Quiang, Wang, and D. J. Unwin. 1992. “Modelling Landslide Distribution on Loess Soils in China: An Investigation.” *International Journal of Geographical Information Systems* 6 (5): 391–405. https://doi.org/10.1080/02693799208901922.

Shuster, Michael, and Jana L Keller. 1993. “Effect of Fire Department First-Responder Automated Defibrillation.” *Annals of Emergency Medicine* 22 (4): 721–27. https://doi.org/10.1016/S0196-0644(05)81856-6.

Singh Walia, Bhavkaran, Michael Madaio, Qianyi Hu, Jeffrey Chen, Fangyan Chen, Jessica Lee, Nathan Kuo, Palak Narang, Jason Batts, and Geoffrey Arnold. 2018. “A Dynamic Pipeline for Spatio-Temporal Fire Risk Prediction.” In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining - KDD ’18*, 764–73. London, United Kingdom: ACM Press. https://doi.org/10.1145/3219819.3219913.

Sircar, Kanta, Jacquelyn Clower, Mi kyong Shin, Cathy Bailey, Michael King, and Fuyuen Yip. 2015. “Carbon Monoxide Poisoning Deaths in the United States, 1999 to 2012.” *The American Journal of Emergency Medicine* 33 (9): 1140–45. https://doi.org/10.1016/j.ajem.2015.05.002.

Smith, K.L., A. Peeters, and J.J. McNeil. 2001. "Results from the First 12 Months of a Fire First-Responder Program in Australia." *Resuscitation* 49 (2): 143–50. https://doi.org/10.1016/S0300-9572(00)00355-5.

Sorensen, John H., Sam A. Carnes, and George O. Rogers. 1992. "An Approach for Deriving Emergency Planning Zones for Chemical Munitions Emergencies." *Journal of Hazardous Materials* 30 (3): 223–42. https://doi.org/10.1016/0304-3894(92)87001-V.

South Carolina Building Codes Council. 2019. "Building Codes in Effect for South Carolina." https://llr.sc.gov/BCC/PDFfiles/Building%20Codes%20in%20Effect%20for%20South%20Carolina.pdf.

Špatenková, Olga, and Alfred Stein. 2010. "Identifying Factors of Influence in the Spatial Distribution of Domestic Fires." *International Journal of Geographical Information Science* 24 (6): 841–58. https://doi.org/10.1080/13658810903143634.

Squire, Benjamin T., Aracely Tamayo, and Joshua H. Tamayo-Sarver. 2010. "At-Risk Populations and the Critically Ill Rely Disproportionately on Ambulance Transport to Emergency Departments." *Annals of Emergency Medicine* 56 (4): 341–47. https://doi.org/10.1016/j.annemergmed.2010.04.014.

Stouffer, John A. 2016. "Community Risk Assessment, A Guide for Conducting a Community Risk Assessment." Version 1.5. Vision 20/20. http://strategicfire.org/wp-content/uploads/2016/04/Community-Risk-Assessment-Guide-v1.5.pdf.

Svenson, James E. 2000. "Patterns of Use of Emergency Medical Transport: A Population-Based Study." *The American Journal of Emergency Medicine* 18 (2): 130–34. https://doi.org/10.1016/S0735-6757(00)90002-0.

Swaroop, Mamta, David C Straus, Carol R Schermer, Ogo Agubuzu, Thomas J Esposito, and Marie L Crandall. 2013. "Pre-Hospital Transport Times and Survival for Hypotensive Patients with Penetrating Thoracic Trauma." *Journal of Emergencies, Trauma, and Shock* 6 (1): 16. https://doi.org/10.4103/0974-2700.106320.

Szlafsztein, Claudio, and Horst Sterr. 2007. "A GIS-Based Vulnerability Assessment of Coastal Natural Hazards, State of Pará, Brazil." *Journal of Coastal Conservation* 11 (1): 53–66. https://doi.org/10.1007/s11852-007-0003-6.

Tate, Eric, Susan L Cutter, and Melissa Berry. 2010. "Integrated Multihazard Mapping." *Environment and Planning B: Planning and Design* 37 (4): 646–63. https://doi.org/10.1068/b35157.

Taylor, Mark John, Emma Higgins, Mike Francis, and Paulo Lisboa. 2011. "Managing Unintentional Dwelling Fire Risk." *Journal of Risk Research* 14 (10): 1207–18. https://doi.org/10.1080/13669877.2011.587884.

Tebeau, Mark. 2003. *Eating Smoke*. Baltimore, MD: The Johns Hopkins University Press.

The Columbia Record. 1985. "What To Look For In '85," January 1, 1985, sec. C. Newsbank: South Carolina Historical Newspapers.

Tobacco Free Kids. 2015. "Tobacco and Socioeconomic Status." Tobacco Free Kids. https://www.tobaccofreekids.org/assets/factsheets/0260.pdf.

Toregas, Constantine, Ralph Swain, Charles ReVelle, and Lawrence Bergman. 1971. “The Location of Emergency Service Facilities.” *Operations Research* 19 (6): 1363–73. https://doi.org/10.1287/opre.19.6.1363.

Turner, Samantha L, Rhodri D Johnson, Alison L Weightman, Sarah E Rodgers, Geri Arthur, Rowena Bailey, and Ronan A Lyons. 2017. “Risk Factors Associated with Unintentional House Fire Incidents, Injuries and Deaths in High-Income Countries: A Systematic Review.” *Injury Prevention* 23 (2): 131–37. https://doi.org/10.1136/injuryprev-2016-042174.

United States Census Bureau. 2018. “QuickFacts: Richland County, South Carolina; United States.” https://www.census.gov/quickfacts/fact/table/richlandcountysouthcarolina,US/PST045218.

Urban Research Institute. 2004. “Lao Urban Fire Risk Assessment Mapping in Vientiane Capital.” Vientiane, Lao: Urban Research Institute. https://www.urban-response.org/system/files/content/resource/files/main/vte-complete.pdf.

U.S. Department of Housing and Urban Development. 2001. “Review of Structural Materials and Methods for Home Building in the United States: 1900 to 2000.” Washington D.C. https://www.huduser.gov/portal/Publications/PDF/review.pdf.

US Department of Transportation, National Highway Traffic Safety Administration (US DOT NHTSA). 2009. “National Emergency Medical Services Education Standards: Emergency Medical Responder Instructional Guidelines.” US Department of Transportation. https://www.ems.gov/pdf/education/National-

EMS-Education-Standards-and-Instructional-Guidelines/EMR_Instructional_Guidelines.pdf.

Vaillancourt, Christian, Ian G Stiell, and Canadian Cardiovascular Outcomes Research Team. 2004. “Cardiac Arrest Care and Emergency Medical Services in Canada.” *The Canadian Journal of Cardiology* 20 (11): 1081–90.

Vega-Garcia, Christina, Paul M. Woodard, and Bryan S. Lee. 1993. “Mapping Risk of Wildfires from Human Sources of Ignition with a GIS.” In *Proceedings, Thirteenth Annual ESRI User Conference.*, 419–26. Redlands, CA: ESRI Press. http://cfs.nrcan.gc.ca/pubwarehouse/pdfs/19132.pdf.

Wallace, Deborah. 1990. “Roots of Increased Health Care Inequality in New York.” *Social Science & Medicine* 31 (11): 1219–27. https://doi.org/10.1016/0277-9536(90)90127-E.

Warda, L., M. Tenenbein, and M. E K Moffatt. 1999. “House Fire Injury Prevention Update. Part I. A Review of Risk Factors for Fatal and Non-Fatal House Fire Injury.” *Injury Prevention* 5 (2): 145–50. https://doi.org/10.1136/ip.5.2.145.

Weaver, Landon, Laura Palombi, and Karen M. S. Bastianelli. 2018. “Naloxone Administration for Opioid Overdose Reversal in the Prehospital Setting: Implications for Pharmacists.” *Journal of Pharmacy Practice* 31 (1): 91–98. https://doi.org/10.1177/0897190017702304.

Xiong, Lin, Dorothy Bruck, and Michelle Ball. 2015. “Comparative Investigation of ‘Survival’ and Fatality Factors in Accidental Residential Fires.” *Fire Safety Journal* 73 (April): 37–47. https://doi.org/10.1016/j.firesaf.2015.02.003.

Young, Tracy, James C. Torner, Kristen C. Sihler, Alfred R. Hansen, Corinne Peek-Asa, and Craig Zwerling. 2003. “Factors Associated with Mode of Transport to Acute Care Hospitals in Rural Communities.” *The Journal of Emergency Medicine* 24 (2): 189–98. https://doi.org/10.1016/S0736-4679(02)00724-2.

Zhou, Yang, Ning Li, Wenxiang Wu, Jidong Wu, and Peijun Shi. 2014. “Local Spatial and Temporal Factors Influencing Population and Societal Vulnerability to Natural Disasters: Population and Societal Vulnerability to Natural Disasters.” *Risk Analysis* 34 (4): 614–39. https://doi.org/10.1111/risa.12193.

APPENDIX A

STATISTICAL COMPARISON OF CENSUS BLOCK GROUPS AND TRACTS

Hypothesis test that the margin of error for ACS Census block groups is smaller than the margin of error for ACS Census tracts.

H_0: $\mu_{T} - \mu_{BG} = 0$

H_A: $\mu_T - \mu_{BG} > 0$

$\alpha = 0.05$

The vast majority of p-values are less than 0.05, thus we can reject the null hypothesis and conclude that most block groups have smaller margins of error than the tracts.

Table A.1: Table of statistics comparing block group and tract margin of error values.
Table is divided into parts only for formatting reasons, with each section having the same rows.

	B01001m1	B01001m2	B01001m3	B01001m4	B01001m5	B01001m6	B01001m8	B01001m9
BG Mean	359.07755	215.33469	45.338776	45.138776	43.326531	33.665306	359.07755	215.33469
BG Min	86	12	6	6	3	2	86	12
BG Max	1672	994	387	281	404	185	1672	994
BG StdDev.P	215.32794	128.66039	44.38178	45.558721	48.576717	33.425797	215.32794	128.66039
Tract Mean	446.88764	305.76404	80.393258	78.280899	74.067416	59.58427	446.88764	305.76404
Tract Min	123	43	12	8	4	9	123	43
Tract Max	1492	1020	390	362	514	226	1492	1020
Tract StdDev.P	222.85176	153.60002	62.685163	63.684614	67.62916	46.035357	222.85176	153.60002
Z_score	3.2122449	4.9580684	4.8522947	4.5083261	3.9352786	4.8659902	3.6570672	4.2921764
p-value	0.0022923	1.832E-06	3.078E-06	1.54E-05	0.000173	2.88E-06	0.0004975	3.985E-05

	B01001m10	B01001m11	B01001m12	B01001m13	B01001m14	B01001m15	B01001m16	B01001m17
BG Mean	45.338776	45.138776	43.326531	33.665306	35.420408	359.07755	215.33469	45.338776
BG Min	6	6	3	2	2	86	12	6
BG Max	387	281	404	185	494	1672	994	387
BG StdDev.P	44.38178	45.558721	48.576717	33.425797	51.773908	215.32794	128.66039	44.38178
Tract Mean	80.393258	78.280899	74.067416	59.58427	63.202247	446.88764	305.76404	80.393258
Tract Min	12	8	4	9	8	123	43	12
Tract Max	390	362	514	226	487	1492	1020	390
Tract StdDev.P	62.685163	63.684614	67.62916	46.035357	73.485943	222.85176	153.60002	62.685163
Z_score	5.0673085	6.4728996	7.2773597	5.7734833	4.3322973	5.1266071	5.2999266	5.8562672
p-value	1.059E-06	3.183E-10	1.261E-12	2.305E-08	3.352E-05	7.831E-07	3.173E-07	1.424E-08

	B01001m18	B01001m19	B01001m20	B01001m21	B01001m22	B01001m23	B01001m24	B01001m25
BG Mean	45.138776	43.326531	33.665306	35.420408	359.07755	215.33469	45.338776	45.138776
BG Min	6	3	2	2	86	12	6	6
BG Max	281	404	185	494	1672	994	387	281
BG StdDev.P	45.558721	48.576717	33.425797	51.773908	215.32794	128.66039	44.38178	45.558721
Tract Mean	78.280899	74.067416	59.58427	63.202247	446.88764	305.76404	80.393258	78.280899
Tract Min	8	4	9	8	123	43	12	8
Tract Max	362	514	226	487	1492	1020	390	362
Tract StdDev.P	63.684614	67.62916	46.035357	73.485943	222.85176	153.60002	62.685163	63.684614
Z_score	4.6503991	4.9525136	5.1487343	5.5609791	4.7048583	5.4117207	3.7099338	3.9313038
p-value	8.032E-06	1.883E-06	6.99E-07	7.687E-08	6.226E-06	1.743E-07	0.0004094	0.0001757
	B01001m26	B01001m27	B01001m28	B01001m29	B01001m30	B01001m31	B01001m32	B01001m33
BG Mean	43.326531	33.665306	35.420408	359.07755	215.33469	45.338776	45.138776	43.326531
BG Min	3	2	2	86	12	6	6	3
BG Max	404	185	494	1672	994	387	281	404
BG StdDev.P	48.576717	33.425797	51.773908	215.32794	128.66039	44.38178	45.558721	48.576717
Tract Mean	74.067416	59.58427	63.202247	446.88764	305.76404	80.393258	78.280899	74.067416
Tract Min	4	9	8	123	43	12	8	4
Tract Max	514	226	487	1492	1020	390	362	514
Tract StdDev.P	67.62916	46.035357	73.485943	222.85176	153.60002	62.685163	63.684614	67.62916
Z_score	4.4362433	5.0467711	4.180129	4.6348757	4.046617	3.640672	3.9620783	3.3995515
p-value	2.125E-05	1.175E-06	6.406E-05	8.633E-06	0.0001109	0.0005281	0.0001556	0.0012341
	B01001m34	B01001m35	B01001m36	B01001m37	B01001m38	B01001m39	B01001m40	B01001m41
BG Mean	33.665306	35.420408	359.07755	215.33469	45.338776	45.138776	43.326531	33.665306

BG Min	2	2	86	12	6	6	3	2
BG Max	185	494	1672	994	387	281	404	185
BG StdDev.P	33.425797	51.773908	215.32794	128.66039	44.38178	45.558721	48.576717	33.425797
Tract Mean	59.58427	63.202247	446.88764	305.76404	80.393258	78.280899	74.067416	59.58427
Tract Min	9	8	123	43	12	8	4	9
Tract Max	226	487	1492	1020	390	362	514	226
Tract StdDev.P	46.035357	73.485943	222.85176	153.60002	62.685163	63.684614	67.62916	46.035357
Z_score	5.7569025	6.4439999	4.9861895	4.3422091	4.3300825	4.9250306	5.679648	5.4232726
p-value	2.536E-08	3.836E-10	1.593E-06	3.211E-05	3.384E-05	2.157E-06	3.945E-08	1.638E-07
	B01001m42	B01001m43	B01001m44	B01001m45	B01001m46	B01001m47	B01001m48	B01001m49
BG Mean	35.420408	359.07755	215.33469	45.338776	45.138776	43.326531	33.665306	35.420408
BG Min	2	86	12	6	6	3	2	2
BG Max	494	1672	994	387	281	404	185	494
BG StdDev.P	51.773908	215.32794	128.66039	44.38178	45.558721	48.576717	33.425797	51.773908
Tract Mean	63.202247	446.88764	305.76404	80.393258	78.280899	74.067416	59.58427	63.202247
Tract Min	8	123	43	12	8	4	9	8
Tract Max	487	1492	1020	390	362	514	226	487
Tract StdDev.P	73.485943	222.85176	153.60002	62.685163	63.684614	67.62916	46.035357	73.485943
Z_score	3.6506886	5.6735858	4.8720115	4.3032848	3.9741726	5.4410143	4.4092436	5.0375309
p-value	0.0005092	4.083E-08	2.796E-06	3.799E-05	0.0001483	1.487E-07	2.395E-05	1.231E-06
	B02001m2	B02001m3	B02001m4	B02001m5	B02001m6	B02001m7	B02001m8	B03003m3
BG Mean	205.35102	268.85714	13.746939	45.955102	14.216327	40.979592	49.979592	73.391837
BG Min	4	8	4	3	6	2	3	2
BG Max	893	1689	92	383	154	397	479	406

BG StdDev.P	148.03405	222.44335	7.6506129	60.791464	14.905626	66.290853	65.264639	83.323231
Tract Mean	282.93258	358.80899	17.483146	85.988764	19.11236	78.101124	96.685393	139.59551
Tract Min	7	11	4	7	6	2	7	5
Tract Max	744	1574	97	383	154	397	500	417
Tract StdDev.P	164.43856	239.0741	12.331664	83.648072	24.121154	96.271158	94.83073	108.2721
Z_score	3.9121489	3.0959576	2.6772314	4.1357163	1.7944586	3.3598205	4.2918219	5.2329572
p-value	0.0001894	0.003308	0.0110788	7.705E-05	0.0797404	0.0014115	3.991E-05	4.514E-07
	B09002m1	B09002m8	B15002m1	B15002m3	B15002m4	B15002m5	B15002m6	B15002m20
BG Mean	143.79592	94.306122	211.79184	13.587755	12.779592	16.967347	16.167347	14.873469
BG Min	8	5	11	2	2	4	2	2
BG Max	906	852	873	58	47	246	156	96
BG StdDev.P	123.1167	101.97147	119.14095	7.3148893	4.4529733	19.928417	14.188547	10.832505
Tract Mean	209.2809	162.75281	274.08989	17.337079	15.078652	25.449438	23.561798	20.842697
Tract Min	12	12	31	2	2	4	2	2
Tract Max	849	871	759	58	47	246	156	123
Tract StdDev.P	143.81558	127.44334	137.05487	11.491026	7.2332328	32.220452	22.653201	17.419412
Z_score	3.81747	4.5637846	3.7984244	2.8738801	2.811276	2.3270787	2.8809892	3.0271627
p-value	0.0002732	1.197E-05	0.0002937	0.0064187	0.007669	0.0266069	0.0062888	0.0040835
	B15002m21	B15002m22	B15002m23	B15002m24	B15002m25	B15002m26	B15002m27	C16002m1
BG Mean	13.383673	14.363265	15.6	14.755102	17.722449	19.820408	19.146939	109.4898
BG Min	4	5	2	4	5	3	4	4
BG Max	60	100	86	75	127	120	120	465
BG StdDev.P	6.1736553	9.6752724	10.664609	9.0249781	14.578867	14.496741	15.400863	61.297975
Tract Mean	16.52809	19.168539	22	21.966292	25	31.325843	31.179775	121.31461

Tract Min	4	5	2	4	4	4	7	4
Tract Max	70	101	86	93	79	143	105	342
Tract StdDev.P	10.032632	15.44489	16.435095	16.754975	17.891056	23.879743	21.52321	61.994308
Z_score	2.7722591	2.7459327	3.4213397	3.8618819	3.4444608	4.2685998	4.843002	1.5457655
p-value	0.0085515	0.0091958	0.0011457	0.0002303	0.0010583	4.408E-05	3.22E-06	0.1207982
	C16002m4	C16002m7	C16002m10	C16002m13	B17017m1	B17017m2	B22010m1	B22010m3
BG Mean	16.481633	13.62449	13.522449	12.310204	109.4898	58.685714	109.4898	32.159184
BG Min	9	6	6	12	4	7	4	7
BG Max	104	89	99	23	465	320	465	138
BG StdDev.P	13.246049	7.0939621	7.6064222	1.4433867	61.297975	40.737327	61.297975	23.698514
Tract Mean	24.426966	17.539326	17.146067	14.067416	121.31461	99.764045	121	39.47191
Tract Min	9	6	6	12	4	12	11	7
Tract Max	104	89	99	23	342	419	303	91
Tract StdDev.P	19.934098	11.141638	12.157719	2.9021408	61.994308	56.965596	57.854137	21.508864
Z_score	3.4906536	3.0947631	2.6309675	5.4716186	1.5457655	6.2473276	1.5818785	2.6719357
p-value	0.0009017	0.0033202	0.0125262	1.258E-07	0.1207982	1.336E-09	0.1141653	0.0112368
	B22010m6	B25001m1	B25003m2	B25002m3	B25002m2	B25014m5	B25014m6	B25014m7
BG Mean	59.97551	109.24898	109.4898	64.004082	83.371429	13.510204	12.453061	12.171429
BG Min	10	4	4	5	4	7	8	12
BG Max	487	487	465	319	455	65	41	19
BG StdDev.P	47.385602	61.078732	61.297975	42.831659	61.246681	5.9044171	2.5190784	0.9406902
Tract Mean	85.752809	73.88764	121.31461	104.50562	115.73034	16.775281	14.292135	13.741573
Tract Min	6	4	4	12	4	7	8	12
Tract Max	358	226	342	329	522	65	41	19

Tract StdDev.P	52.293313	39.076542	61.994308	57.458363	79.347729	9.2356817	4.3166837	2.5419098
Z_score	4.081333	-6.2138865	1.5457655	6.0657788	3.4882739	3.1121429	3.7915488	5.6876315
p-value	9.634E-05	1.646E-09	0.1207982	4.086E-09	0.0009092	0.0031459	0.0003015	3.77E-08
	B25014m11	B25014m12	B25014m13	B25034m2	B25034m3	B25034m4	B25034m5	B25034m6
BG Mean	16.008163	12.955102	12.910204	17.685714	26.640816	55.510204	54.453061	52.314286
BG Min	6	8	8	6	5	6	5	5
BG Max	112	48	68	120	205	531	392	250
BG StdDev.P	12.419534	3.8968884	4.9889774	16.715971	31.291936	67.071489	56.629721	42.370321
Tract Mean	22.831461	15.775281	15.494382	25.764045	44.449438	94.134831	93.179775	86.977528
Tract Min	6	8	8	6	5	10	7	7
Tract Max	148	52	68	156	266	713	563	280
Tract StdDev.P	19.913993	6.5114468	8.0099988	26.682495	45.998293	97.370737	85.856238	62.612771
Z_score	3.0257466	3.8435642	2.8494221	2.6720735	3.37941	3.4562081	3.9543206	4.8360068
p-value	0.0041011	0.0002472	0.0068841	0.0112327	0.0013213	0.0010163	0.0001605	3.33E-06
	B25034m7	B25034m8	B25034m9	B25034m10	B25034m11	B27010m1	B27010m6	B27010m7
BG Mean	58.04898	45.942857	37.110204	26.857143	25.089796	346.55102	12.220408	99.730612
BG Min	4	6	10	4	7	12	6	8
BG Max	187	202	141	158	123	1690	32	499
BG StdDev.P	35.484254	31.158266	26.125601	21.613677	20.956907	218.93073	1.6011449	91.330488
Tract Mean	92.123596	74.235955	60.988764	44.05618	40.685393	431.55056	13.764045	170.85393
Tract Min	12	6	12	4	7	19	6	12
Tract Max	230	219	172	169	141	1487	32	503
Tract StdDev.P	55.464296	46.513988	39.131726	31.088984	31.705667	235.21441	3.2395813	121.72252

Z_score	5.4076917	5.3210945	5.3405521	4.813567	4.3109474	2.9732594	4.3081383	5.0226274
p-value	1.782E-07	2.835E-07	2.556E-07	3.711E-06	3.676E-05	0.0048003	3.721E-05	1.327E-06
	B27010m13	B27010m17	B27010m22	B27010m23	B27010m29	B27010m33	B27010m38	B27010m39
BG Mean	12.183673	24.738776	12.428571	42.363265	12.771429	65.016327	20.416327	35.163265
BG Min	5	6	7	3	6	6	6	2
BG Max	22	207	43	329	65	313	171	272
BG StdDev.P	1.3259339	28.646137	2.6232866	46.0939	5.0834666	54.328702	20.446599	33.304009
Tract Mean	13.719101	42.707865	14.280899	79.898876	15.280899	116.40449	33.842697	62.393258
Tract Min	5	6	7	7	6	11	6	2
Tract Max	22	240	43	329	65	313	173	306
Tract StdDev.P	2.9451494	43.488653	4.5146174	64.112795	8.2720441	75.527913	30.762555	47.430284
Z_score	4.7466781	3.6229522	3.6531651	5.0678994	2.6837865	5.8891087	3.8221907	4.9878196
p-value	5.109E-06	0.0005632	0.0005046	1.056E-06	0.0108858	1.175E-08	0.0002683	1.58E-06
	B27010m46	B27010m50	B27010m55	B27010m62	B27010m66			
BG Mean	20.106122	59.934694	38.714286	18.922449	12.289796			
BG Min	2	4	2	3	3			
BG Max	261	391	273	150	39			
BG StdDev.P	22.803441	54.901506	31.928875	16.364662	3.0050464			
Tract Mean	33.52809	108.23596	64.573034	29.752809	13.786517			
Tract Min	4	9	7	3	3			
Tract Max	261	391	330	180	39			
Tract StdDev.P	35.012707	77.443712	48.286571	25.246773	5.2413051			
Z_score	3.3664001	5.4107143	4.6931654	3.7695366	2.5462524			
p-value	0.0013806	1.753E-07	6.578E-06	0.0003276	0.0155976			

APPENDIX B

GIS AND STATISTICAL PROCESSING WORKFLOWS

Step by step information on GIS and statistical processing, include which software tools were used, and what their inputs were. Instructions are written for the GIS user who is reasonably experienced with ArcGIS. For additional questions about specific GIS tools see online documentation provided by Esri.

B.1 General Notes

1. Reproject all data sets into the same projection before beginning any preprocessing or analysis. This research used NAD 83 UTM 17N, but this will vary depending on location and the datum used by most layers.

B.2 Populated Block Groups

1. Select only Richland county block groups (export these as their own new layer)
2. Erase military bases, Irmo, and nonpopulated areas
    a. Nonpopulated areas: Select blocks with no population and no households (because areas under development tend to have at least one household even if no people)

b. Merge all three relevant layers (i.e., Irmo, military, nonpopulated) for efficiency in clipping the block groups and reducing intermediate output layers

3. Calculate Census columns as described in Appendix C

B.3 Tidy Military Boundaries

1. Buffer inwards by 100ft to shift off of roads that act as property line (e.g. Leesburg Road)
2. Tidy boundaries so as not to have disconnected areas
    a. Remove pocket of forest inside McEntire (let it count as part of McEntire)
    b. Remove bump in on north side at McEntire and extend corner in SW side of Jackson that cut off road sections, that would otherwise leave an unattached road segment in the analysis area

B.4 Service Area Creation

1. Road network prep
    a. Start with US Census 2019 TIGER roads for Richland plus surrounding counties (Fairfield, Kershaw, Lexington). Calhoun, Newberry, and Sumter can be excluded because no Richland roads require crossing into these neighboring counties.
        i. Trim most parts of neighboring counties that aren't relevant to Richland access to speed processing time

    ii. Don't clip roads to exact county boundaries because this cuts off some roads in the county near the county line

b. Check for disconnected roads, update based on underlying Esri images (adding roads visible in the imagery) – this was done by looking for wonky service area results

c. Extend a few segments way out past the county border (including places like Congaree with no actual connections) so that service areas are computed past the edge of the county in areas with minimal roads.

2. Create service areas for engines/ladders/tankers (one service area for each type of apparatus)

    a. Create dataset (to hold roads network)

    b. Add roads feature class to dataset

    c. Create network dataset from polyline shapefile of Richland County roads (http://desktop.arcgis.com/en/arcmap/latest/extensions/network-analyst/exercise-1-creating-a-network-dataset.htm)

        i. Make sure to use every vertex not just end points

        ii. Set length attribute to miles

        iii. Auto build network dataset

    d. Create New Service Area (tutorial: http://desktop.arcgis.com/en/arcmap/10.3/guide-books/extensions/network-analyst/service-area.htm)

    e. Add Facilities (each apparatus type) (see tutorial)

    f. Add polygon barriers (military boundaries)

g. Set Service Area Properties (Network Analyst window – see tutorial)
    i. For each type of apparatus separately do increments of 0.1 miles far enough to cover the entire county (15 miles needed for engines and tankers, 30 miles needed for ladders)
    ii. Polygons: detailed, merge by break value, overlap as rings
h. Solve network analysis
i. At this point tankers divert to hydrant section below
j. Rasterize polygons – 15m cell to match with 50ft hose lengths, max combined area
    i. FromBreak = distance value

3. Calculate average distance to apparatus per block group
    a. Use "Zonal Statistics to Table" to calculate averages per populated block group

B.5 Hydrants

1. 1000ft buffer around hydrants
2. Union tanker service areas and hydrant 1000ft buffer
    a. Distance to water supply is zero if within 1000ft of a hydrant, otherwise use the distance to the nearest tanker
        i. New attribute column: distance=FromBreak, then where hydrantbufferID = 1 set distance to 0
3. Rasterize polygons – 15m cell to match with 50ft hose lengths, max combined area

a. Use distance as raster value

B.6 <u>Railroad Grade Crossings</u>

1. Create railroad crossing layer
    a. Intersect rail and roads layer, point output
    b. Multipart to Singlepart on crossings layer
    c. Manually look at each crossing over imagery (Esri, Google, Google Earth) to ID at/above/below grade crossing
        i. When no road crossing is visible because the road line seems over extended based on all available imagery update the road line to match imagery
2. Count railroad grade crossings in route from the nearest engine
    a. Follow steps above to create a service area for the engines covering their maximum territory
        i. Facilities = engines
        ii. Polygon barriers = military
        iii. Single 15 mile break point
        iv. Polygons detailed, not overlapping, rings (or disks – doesn't matter)
    b. Manually split polygons to break by minimum number of grade crossings between location and nearest engine

i. Where shortest route has multiple grade crossings but an alternate route exists to the same closest station with fewer grade crossings take the lower value

ii. For edge areas with no roads, base polygon off of nearest road, even if that road is technically in a different engine's area

c. Tidy edges and weird donut bits along the way, including making the boundaries align with the Broad River

B.7 Geocode NFIRS Data

1. Extract NFIRS data to Excel via Access database (thank you Samantha Quizon and Kirsten Therrien for assistance)
2. Select only calls of interest prior to geocoding to reduce dataset size
    a. 111 – building fire
    b. 112 – fire in non-building structure (tunnels, bridges, utility vaults, piers, etc.)
    c. 113 – cooking fire (contained)
    d. 114 – chimney fire (contained)
    e. 115 – incinerator fire (contained)
    f. 116 – boiler fire (contained)
    g. 117 – trash compactor fire (fire confined to rubbish)
    h. 118 – rubbish fire in structure, no flame damage
    i. 121 – mobile home fire
    j. 122 – RV home fire

    k. 123 – portable building fire
    l. 311 – med assist
    m. 321 – EMS (not MVC)
    n. 424 – CO
    o. Remove “mutual aid given”
    p. Remove non CRFD districts (i.e., station territories) (anything other than a number)
    q. Remove no street listed and “unknown street name”
    r. Remove no street number/mile marker listed (or listed as 0)
    s. Remove interstate addresses (especially since Esri can’t seem to get them down to a single milemarker location, and they all ended up geocoded at Score<=95 anyways)
    t. Manually update address formatting as needed
        i. Don’t worry about addresses with street_type included in street_name since they’re going to be combined anyways
        ii. Manually edit addresses with town included in street_name too
        iii. Correct “CR” to “CIR”
3. Geocode addresses
    a. Format address data into single column (street num, IN_prefix, street, street_type, IN_suffix, city, added SC, zip – with proper comma placement) (70562 records)
    b. ArcGIS geocoding
        i. Sign in with login

    ii. Right click layer
    iii. Geocode Addresses
    iv. Esri World Geocoder
c. Further address cleaning discovered by first ArcGIS geocode pass (232 of 70562 at less than 95% accuracy)
    i. focus on correcting addresses geocoded to zipcode or street only level
        1. use Google Maps to assist in identifying typos, cut-off names, etc.
    ii. ID some with correct name (according to Google Maps) but which ArcGIS couldn't identify
    iii. Manually geocode all ArcGIS-misidentified points using Google Maps
        1. Census Geocoder did a pretty miserable job when attempted (worse than Google Maps)
        2. Update Match_Addr to corrected name (when applicable)
        3. Update Match_type to "M" (manual)
    iv. clear many addresses as good (e.g. missing directional marker in original name, but correctly located) (set Match_type=AG -> "A-good")
    v. 25 addresses could not be distinctly ID'd by ArcGIS or Google -> deleted

B.8 Hot Spot Analysis

1. ArcGIS -> Spatial Statistics -> Mapping Clusters -> Generate Spatial Weight Matrix
    a. Fixed Distance Band (based on Esri modeling spatial relationship guidelines)
    b. Threshold = 4000 meters (ran incremental spatial autocorrelation on non-spatial outliers (i.e., polygon area within 3 STD of mean area) with start and increment of 1000 on each type of call. 4000 was peak for overall, mid-point for injury/fatality vs fire overall)
    c. # Neighbors = 3 -> most of the spatial outliers had at least three edge neighbors
    d. Steps a. to c. as a sentence: neighborhood defined as either all block groups within four kilometers, or a minimum of three neighbors in areas with more widely spaced block groups.
2. ArcGIS -> Spatial Statistics -> Mapping Clusters -> Anselin Local Morans I
    a. Neighborhood based on spatial weight matrix
    b. Other parameters as default

B.9 PCA

1. SPSS Analyze->Dimension Reduction -> Factor
    a. Risk factors
        i. Run on z-scores instead of absolute numbers
        ii. See Section 3.4 and Table 3.3 for details on included risk variables

iii. See Table B.1 for details on the sixteen different PCA trials that were run

b. Input parameters (based on SoVI calculation guidelines)

i. Max iterations to convergence = 100 (Extraction and Rotation tabs)

ii. Varimax rotation

iii. Display scree and loading plots

iv. Factor Scores -> Save as variables -> Regression

1. appends them to the original dataset (only did this for the best/highlighted run below)

v. All other inputs as default

B.10 K-Means

1. ArcGIS -> Spatial Statistics -> Mapping Analysis -> Grouping Analysis

a. Use all risk variables

b. Use "Evaluate Optimal Number of Groups"

c. No spatial constraints

d. Otherwise use defaults

Table B.1: Risk variable variations run through PCA with percent variable explained and number of principal factors.

PCA Run	Variables Included	Percent Explained Variance	Number of Principal Factors
1	Total Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 50 years	69.933%	9

2	Total Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 50 years	70.318%	9
3	Avg. Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 50 years	70.017%	9
4	Avg. Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 50 years	70.375%	9
5	Total Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 70 years	68.776%	9
6	Total Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 70 years	69.161%	9
7	Avg. Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 70 years	68.921%	9
8	Avg. Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 70 years	69.304%	9
9	Total Alcohol and Smoking, Under 8th Grade Education, Age thresholds 18 and 50 years	70.740%	9
10	**Total Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 50 years***	**71.207%**	**9**
11	Avg Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 50 years	67.960%	8
12	Avg Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 50 years	68.411%	8
13	Total Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 70 years	70.320%	9
14	Total Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 70 years	70.682%	9
15	Avg Alcohol and Smoking, Under 8th Grade Education, Age thresholds 5 and 70 years	70.619%	9
16	Avg Alcohol and Smoking, No H.S. Diploma or GED, Age thresholds 5 and 70 years	70.993%	9

* Bolded run had the greatest explained variance.

APPENDIX C

CENSUS COLUMN CALCULATIONS

Table C.1: Equations for how Census-derived risk variables were calculated from multiple columns of ACS data

Risk Variable	ACS Column Equation
Owner Occupied	B25003e2 / B25001e1
Vacant	B25002e3 / B25001e1
Crowded	sum(B25014e5, B25014e6, B25014e7, B25014e11, B25014e12, B25014e13) / B25002e2
Under 8th Grade Education	sum(B15002e3, B15002e4, B15002e5, B15002e6, B15002e20, B15002e21, B15002e22, B15002e23) / B15002e1
No Diploma	sum(B15002e3, B15002e4, B15002e5, B15002e6, B15002e7, B15002e8, B15002e9, B15002e10, B15002e20, B15002e21, B15002e22, B15002e23, B15002e24, B15002e25, B15002e26, B15002e27) / B15002e1
Single Parents	B09002e8 / B09002e1
Poverty	B17017e2 / B17017e1
Under 5	sum(B01001e3, B01001e27) / B01001e1
Under 10	sum(B01001e3, B01001e4, B01001e27, B01001e28) / B01001e1
Under 18	sum(B01001e3, e4, e5, e6, e27, e28, e29, e30) / B01001e1
Age 6 to 49	sum(B01001e4, B01001e5, B01001e6, B01001e7, B01001e8, B01001e9, B01001e10, B01001e11, B01001e12, B01001e13, B01001e14, B01001e15, B01001e28, B01001e29, B01001e30, B01001e31, B01001e32, B01001e33, B01001e34, B01001e35, B01001e36, B01001e37, B01001e38, B01001e39) / B01001e1
Age 18 to 49	sum(B01001e7, B01001e8, B01001e9, B01001e10, B01001e11, B01001e12, B01001e13, B01001e14, B01001e15, B01001e31, B01001e32, B01001e33, B01001e34, B01001e35, B01001e36, B01001e37, B01001e38, B01001e39) / B01001e1
Age 6 to 69	sum(B01001e4, B01001e5, B01001e6, B01001e7, B01001e8, B01001e9, B01001e10, B01001e11, B01001e12, B01001e13, B01001e14, B01001e15, B01001e16, B01001e17, B01001e18, B01001e19, B01001e20, B01001e21, B01001e28, B01001e29, B01001e30, B01001e31, B01001e32, B01001e33, B01001e34, B01001e35, B01001e36, B01001e37, B01001e38, B01001e39,

	B01001e40, B01001e41, B01001e42, B01001e43, B01001e44, B01001e45) / B01001e1
Age 18 to 69	sum(B01001e7, B01001e8, B01001e9, B01001e10, B01001e11, B01001e12, B01001e13, B01001e14, B01001e15, B01001e16, B01001e17, B01001e18, B01001e19, B01001e20, B01001e21, B01001e31, B01001e32, B01001e33, B01001e34, B01001e35, B01001e36, B01001e37, B01001e38, B01001e39, B01001e40, B01001e41, B01001e42, B01001e43, B01001e44, B01001e45) / B01001e1
Age 20 to 69	sum(B01001e8, B01001e9, B01001e10, B01001e11, B01001e12, B01001e13, B01001e14, B01001e15, B01001e16, B01001e17, B01001e18, B01001e19, B01001e20, B01001e21, B01001e32, B01001e33, B01001e34, B01001e35, B01001e36, B01001e37, B01001e38, B01001e39, B01001e40, B01001e41, B01001e42, B01001e43, B01001e44, B01001e45) / B01001e1
Over 50	sum(B01001e16, B01001e17, B01001e18, B01001e19, B01001e20, B01001e21, B01001e22, B01001e23, B01001e24, B01001e25, B01001e40, B01001e41, B01001e42, B01001e43, B01001e44, B01001e45, B01001e46, B01001e47, B01001e48, B01001e49) / B01001e1
Over 65	sum(B01001e20, B01001e21, B01001e22, B01001e23, B01001e24, B01001e25, B01001e44, B01001e45, B01001e46, B01001e47, B01001e48, B01001e49) / B01001e1
Over 70	sum(B01001e21, B01001e22, B01001e23, B01001e24, B01001e25, B01001e45, B01001e46, B01001e47, B01001e48, B01001e49) / B01001e1
Over 75	sum(B01001e22, B01001e23, B01001e24, B01001e25, B01001e46, B01001e47, B01001e48, B01001e49) / B01001e1
Over 80	sum(B01001e24, B01001e25, B01001e48, B01001e49) / B01001e1
Over 85	sum(B01001e25, B01001e49) / B01001e1
White	B02001e2 / B01001e1
Black	B02001e3 / B01001e1
Native American	B02001e4 / B01001e1
Asian	sum(B02001e5, e6) / B01001e1
Other/Two+ Races	sum(02001e7, e8) / B01001e1
Hispanic	B03003e3 / B01001e1
One/Two Family	sum(B25032e3, B25032e4, B25032e5, B25032e14, B25032e15, B25032e16) / B25032e1
Multi Family	sum(B25032e6, B25032e7, B25032e8, B25032e9, B25032e10, B25032e17, B25032e18, B25032e19, B25032e20, B25032e21) / B25032e1
Mobile Home	sum(B25032e11, B25032e22) / B25032e1
Vehicle Home	sum(B25032e12, B25032e23) / B25032e1

No Insurance	sum(B27010e17, B27010e33, B27010e50, B27010e66) / B27010e1
Medicaid/care Insurance Only	sum(B27010e6, B27010e7, B27010e13, B27010e22, B27010e23, B27010e29, B27010e38, B27010e39, B27010e46, B27010e55, B27010e62) / B27010e1
Poor English	sum(C16002e4, C16002e7, C16002e10, C16002e13) / C16002e1
Old House	B25034e11 / B25034e1
Postwar House	sum(B25034e7, B25034e8, B25034e9, B25034e10) / B25034e1
Late 20th Cen. House	sum(B25034e5, B25034e6) / B25034e1
Early 21st Cen. House	sum(B25034e2, B25034e3, B25034e4) / B25034e1
Disabled Household	sum(B22010e3, B22010e6) / B22010e1